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Chapter 1: Pollution Control Using Emission Performance Standards: Evidence from the Large Combustion Plant Directive

- Chapter 1 is based on a single-authored unpublished paper. It is a slightly modified version of a working paper, published as a DIW Discussion paper (Singhal, 2019).
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Chapter 2: Inform Me When It Matters: Cost Salience, Energy Consumption, and Efficiency Investments

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Chapter 1

Introduction

In this dissertation, I contribute to three strands of the environmental economics literature: (1) regulation of air pollution from stationary sources, (2) interaction between behavioral biases and consumer demand for energy, and (3) long-term distributional outcomes of policies that seek to mitigate climate damages from the housing sector.

The first paper looks at how environmental regulations work in practice – assessing ex-post the causal consequences of a specific policy, the Large Combustion Plant Directive. The Large Combustion Plant Directive was a key policy instrument to limit air pollution from power stations in the European Union. The Directive set limits on emissions of harmful sulfur dioxide, nitrogen oxide and particle dust from combustion plants with total capacity of at least 50 MWth. A fundamental empirical problem is to create a valid counterfactual, to understand what would have happened in the absence of such a regulation. As is the case with most command and control policies, all plants fell under regulation, but the stringency was vintage-differentiated. More crucially, a group of plants chose to opt-out of emissions performance standards but were instead required to gradually cease operations. I exploit the structure of the directive to construct valid control groups to assess the effectiveness of emission performance standards. Evidence from this empirical study suggests that EU-wide emission performance standards, when sufficiently stringent, are an effective instrument for pollution abatement at the plant stack-level. However, the regulation was not ambitious enough and in fact allowed business-as-usual operations for some of the most carbon-intensive power plants operating in the European Union.

In the second paper, I exploit a large-scale natural experiment in utility billing cycles at the building level to identify the salience effect of costs on energy consumption. By exploiting variation in billing cycles, I find new evidence for consumer inattention to energy costs: consumers that are billed for heating during off-winter months demand more heat energy annually. Results show that households are paying attention to their heating costs in the first three months of the 12-month billing period. As a result, bills immediately before the winter heating season are most effective, allowing ample opportunity to adjust consumption. I show that salience bias in annual heat energy demand is persistent and pervasive – affecting households in all regions and building/technology type. Enduring differences in consumer inattention to energy costs led to significantly higher heating expenditures for buildings treated with summer billing cycles. Differences in efficiency investments across billing cycles highlight that, at least for multi-apartment buildings, owners of buildings did invest towards closing any perceived energy-efficiency gaps, which were driven by consumer misoptimization by tenants, treated with low salience of energy bills.

In the third paper, which is joint work with Andrew Hobbs, we examine the effect of temperature on residential heat demand and the spatial distribution of energy (in)efficient buildings in Germany. To uncover the underlying thermal efficiency of buildings, we estimate the causal response of building-level heat demand to variability in heating degree days. We examine heterogeneity in temperature response using both standard econometrics and causal forests to identify differences in energy-efficiency between buildings and regions. Without making any functional form assumptions, we are able to account for observable and unobservable characteristics that are likely drivers of the realized energy-efficiency outcomes. Results show that the distribution of energy-efficiency is not equitable in the West of Germany, with buildings located in Bavaria and Baden Württemberg attaining the best energy performance standards nationwide. Compared to the West, the East of Germany is home to a significantly higher share of older buildings that were not subject to building codes. Notwithstanding, they perform better than the West counterpart, likely as a result of large investments in retrofitting post-reunification. We highlight that the highest untapped potential for gains in energy-efficiency is located in the North-West of Germany.

1.1 Deutsche Zusammenfassung

Die vorliegende Dissertation besteht aus drei empirische Kapiteln, die zur umweltökonomischen Literatur beitragen: (1) Regulierung der Luftverschmutzung durch stationäre Quellen, (2) die Interaktion zwischen Verhaltensverzerrungen und Verbrauchernachfrage nach Energie sowie, (3) langfristige Verteilungswirkungen von Maßnahmen zur Minderung von Klimaschäden durch den Wohnungssektor.

Das erste Kapitel bewertet ex post die kausalen Effekte einer bestimmten umweltpolitischen Maßnahme, nämlich der Großfeuerungsanlagenverordnung. Die Richtlinie Large Combustion Plant Directive ist ein wichtiges politisches Instrument zur Begrenzung der Luftverschmutzung durch Kraftwerke in der Europäischen Union. Die Verordnung legt Grenzwerte für die Emissionen von schädlichem Schwefeldioxid, Stickoxid und Partikelstaub aus Feuerungsanlagen mit einer Gesamtkapazität von mindestens 50 MWth fest. Ein grundlegendes empirisches Problem besteht darin, ein gültiges Kontrafaktum zu schaffen, um zu verstehen, was ohne eine solche Regelung geschehen wäre. Wie bei den meisten command-and-control fielen alle Anlagen unter die Regulierung, aber die Stringenz war vintage-differenziert. Entscheidender ist an dieser Stelle, dass einige Anlagenbetreiber die Emissionsgrenzwerte ablehnten und daher den Betrieb schrittweise einstellen mussten. Ich nutze diese Struktur der Richtlinie, um gültige Kontrollgruppen zur Bewertung der Wirksamkeit von Emissionsgrenzwerten zu untersuchen. Aus dieser empirischen Studie geht hervor, dass EU-weite Emissionsgrenzwerte, wenn sie ausreichend streng sind, ein wirksames Instrument zur Verringerung der Umweltverschmutzung darstellen. Die Verordnung war jedoch nicht ehrgeizig genug und erlaubte sogar einigen der kohlenstoffintensivsten Kraftwerke in der Europäischen Union den normalen Betrieb.

Im zweiten Kapitel nutze ich Varianz in den Abrechnungszeiträumen von Versorgungsunternehmen auf Gebäudeebene in einem natürlichen Experiment, um den Salienzeffekt der Kosten auf den Energieverbrauch zu ermitteln. Ich finde neue empirische Evidenz für einen Mangel an Aufmerksamkeit von Verbrauchern gegenüber den Kosten ihres Energieverbrauchs: Verbraucher, denen ihr Wärmeverbrauch in den Monaten außerhalb der Wintermonate in Rechnung gestellt wird, verbrauchen jährlich mehr Wärmeenergie. Die Ergebnisse zeigen, dass Haushalte in den ersten drei Monaten des 12-monatigen Abrechnungszeitraums auf ihre Heizkosten achten. Infolgedessen sind Rechnungen unmittelbar vor der Heizsaison im Winter am effektivsten, was reichlich Gelegenheit zur Anpassung des Energieverbrauchs bietet. Ich zeige, dass der Salienz-Bias des jährlichen Heizenergiebedarfs persistent ist und Haushalte in allen Regionen und Gebäude- und Technologietypen betrifft. Anhaltende Unterschiede in der Unaufmerksamkeit der Verbraucher in Bezug auf ihre Energiekosten führten zu erheblich höheren Heizkosten für Wohngebäude mit Abrechnungsdatum im Sommer. Unterschiede bei den Effizienzinvestitionen über die Abrechnungszeiträume hinweg machen deutlich, dass zumindest bei Gebäuden mit mehreren Wohnungen, die Eigentümer zur Schließung von Lücken in der Energieeffizienz investierten, die durch einen Mangel an Verbrauchsoptimierung durch die Mieter verursacht wurden.

Im dritten Artikel, den ich gemeinsam mit Andrew Hobbs verfasst habe, untersuchen wir den Einfluss der Temperatur auf den Wärmebedarf von Wohngebäuden und die regionale Verteilung von energie(in)effizienten Wohngebäuden in Deutschland. Um die zugrunde liegende thermische Effizienz von Gebäuden aufzudecken, schätzen wir die kausale Reaktion des gebäudebezogenen Wärmebedarfs auf die Variabilität der Heizgradtage. Wir untersuchen Effektheterogenitäten sowohl mittels ökonometrischer Standardmethoden als auch mit Hilfe von "Causal Forests", um Unterschiede in der Energieeffizienz zwischen Gebäuden und Regionen zu identifizieren. Die Ergebnisse zeigen, dass die Verteilung der Energieeffizienz in Westdeutschland ungleich verteilt ist, wobei Wohngebäude in Bayern und Baden Württemberg bundesweit die besten Energieeffizienzstandards erreichen. Im Vergleich zum Westen weist der Osten Deutschlands einen deutlich höheren Anteil an älteren Wohngebäuden auf, die nicht der Wärmeschutzverordnung unterlagen. Dennoch schneiden sie im Schnitt besser ab als ihre westlichen Pendants, was wahrscheinlich auf die hohen Investitionen in die Sanierung nach der Wiedervereinigung zurückzuführen ist. Wir weisen darauf hin, dass das höchste ungenutzte Potenzial zur Steigerung der Energieeffizienz im Nordwesten Deutschlands liegt.

Chapter 2

Pollution Control Using Emission Performance Standards: Evidence from the Large Combustion Plant Directive

2.1 Introduction

Fossil-fuel combustion for power generation is the largest source of global greenhouse gas emissions, but also a significant common source of local air pollution. In the European Union (EU), the energy production and distribution sector is one of the major emitters of toxic pollutants such as sulfur dioxide (SO_2) and nitrogen oxides (NOx), which are known to damage ecosystems and detrimental to human health (EEA, 2017). To regulate environmental and health damages by thermal power plants, the European Commission adopted a number of policy instruments[1], including the Large Combustion Plant (LCP) Directive, a command-and-control (CAC) regulation[2] intended to control emission intensities of SO_2, NOx, and particulate matter (dust) from large power stations in both the energy and industrial sectors.

The negative impact of air pollution on human health is of increasing concern and the LCP directive was a major environmental regulation to control pollutants from EU com-

[1]The EU community also established its first cap-and-trade program in 2005, a multinational emissions trading scheme (EU ETS) to control carbon dioxide (CO_2) emissions, along with country-level caps on CO_2 emissions from all thermal combustion plants generating electricity larger than 20 MWth (Martin et al. 2016).

[2]CAC instruments are a direct form of regulation in which the regulator specifies a target or a standard that a firm, plant, or locality must achieve – or face non-compliance penalties. Between 1970 and 2011, over 50% of EU environmental policy instruments used were of the CAC type (regulatory, interventionist, and topdown), with emission limits and technical requirements playing the role of the top two (Schmitt and Schulze, 2011).

bustion plants. In contrast to a large body of literature on air pollution regulation in other countries (see Section 2.2), we know considerably little about the policy impact of command-and-control policies in the EU which have been used for decades in controlling local pollution from fossil-fuel power plants. Quantifying the causal effects of conventional regulation such as the LCP directive is essential to accurately evaluating the benefits of overlapping environmental instruments and (re-)designing them to meet the increasingly challenging public health and climate policy goals in the future. For example, the Industrial Emissions Directive (IED 2010/75/EU) succeeds and tightens the provisions in the LCP directive and the corresponding emission performance standards (EPS) were applicable to all existing combustion plants, effective in 2016.

This paper offers the first impact assessment of the Large Combustion Plant directive on flue emissions rates from thermal combustion plants in the European Union[3]. The LCP directive set mandatory minimum EPS for SO_2, NOx, and total particulate matter, which applied to all combustion plants with a rated thermal input of 50 MW or more. I examine the following research questions in this paper: 1) How effective were the EPS under the LCP Directive in cleaning up emissions from the oldest existing stock of EU combustion plants? 2) To what extent did stricter standards prompt the newest plants towards cleaner technology choices for fuel combustion? 3) Did the opt-out policy actually encourage the old, large, and dirty combustion units to eventually close operations?

The key challenges in answering these questions are separating the effects of the LCP Directive from the 2008 economic crisis, the EU ETS, the National Emission Ceilings (NEC) Directive, the policy interaction with the Integrated Pollution Prevention and Control (IPPC) Directive, along with time-varying confounding factors leading to selection bias in estimating treatment effects. Notwithstanding, a number of regulation-specific factors makes the LCP Directive an ideal policy to study in order to understand the effectiveness of emission performance standards on the full population of combustion plants in the EU. First, the directive had three distinct regulation arms: Articles 4-1, 4-2, and 4-3. Regulation intensity was differentiated across plants based on the operation licensing dates – this allowed us to construct plausible counterfactuals and evaluate the effect of emission performance standards at both the extensive and intensive margins.

Second, the LCP directive differed from the usual vintage-differentiated regulation in the United States (see Stavins 2006), because it did not exempt older plants from any form of regulatory intervention. This allowed us to investigate the environmental performance of

[3] This paper does not assess the (incomplete) compliance rate across combustion plants, industries, or Member States covered under the LCP regulation. For a useful report on the subject of compliance, see Wynn and Coghe (2017). They assess emission concentrations from the dirtiest non-compliant coal-fired power plants in Europe and discuss the implications that the new round of emission limits under the EU's Industrial Emission Directive have on their operation decisions.

the oldest combustion plants in the European Union. All plants licensed before July 1987 were required under the provisions of Article 4-3 to either 1) take appropriate measures to achieve annual emissions concentrations established under Article 4-1, 2) be included under a national emission reduction plan (NERP), or 3) opt-out from emission limits values (ELV) to instead limit operation hours to 20,000 and be required to shut down by the end of 2015. I treat opt-out plants as the control group to estimate the effect on stack-level emission concentrations of older plants (Article 4-3) that chose to comply with new environmental standards (ELV treatment). Using difference-in-differences, I find that average SO_2, NOx, and dust emission concentrations were 39%, 10%, and 25% lower respectively after the policy deadline. Furthermore, keeping the same counterfactual of opt-out plants, I find that emissions intensity of relatively newer plants under Article 4-1 did not change significantly (with the exception of SO_2 concentrations). Consequently, I argue that the response of the oldest fleet under Article 4(3) to emission standards was much stronger than that from Article 4(1) plants.

Third, the directive took the form of a typical CAC regulation in which the prescribed emission limits are more stringent for newly built plants than for existing plants. Combustion plants that were brought into operation between July 1987 and November 2003 were subject to lenient emission standards laid down in Article 4(1). Meanwhile, newer plants that started to operate post November 2002 were subject to significantly tighter emission limits values under Article 4(2). I am unable to apply the core D-i-D empirical model, used to evaluate the response to standards applied under Articles 4-3 and 4-1, because new plant operators could have anticipated the regulation before the compliance deadline of 2008. There are strong reasons for this. There is a time gap between when the directive was issued (2001) and the effective date of compliance (2008), possibly giving rise to anticipation effects for plants built after LCPD was issued. Anticipation of standards is much more plausible for new plants than old plants because upgrading or retrofitting older combustion units is costlier and takes more time. New plant operators had perfect foresight of the EPS required under the LCP directive before the policy deadline of 2008, therefore pre-trends in emissions concentrations could be potentially contaminated if operators made early clean investments in anticipation.

Another reason for anticipation is the policy interaction with the IPPC directive - which required permits to operate new combustion plants or make changes to existing installations since 30 October 1999. The IPPC necessitated compliance with emission performance standards under the LCP directive. Unfortunately, I only observe emissions and plant-level operations starting in 2004 and therefore am unable to observe the full impact of the directive pre-deadline. Nevertheless, I take into account that plants were not completely myopic and investigate the difference in response to standards of plants that were licensed close to the date of 2003, starting when plants were subject to Article (2). The variation in performance standards across plants (near the 2003 cutoff date) offers us a natural experiment that mitigates selection bias. I treat plants subject to the provisions under Article 4-1 as baseline, against which I compare emissions intensity of plants under Article 4(2), to answer whether combustion plants subject to more stringent EPS were progressively cleaner due to the policy. I find strong evidence that tighter standards prompted newer plants to reduce emission concentrations of local pollutants from 2004 to 2015.

To my knowledge, Meyer and Pac (2017) is the only paper to empirically explore the consequences of the LCPD regulation in the European Union. It focus on correlation rather than causation, however. The main result suggests that higher coal or lignite fuel input at power-generating plants was associated with a lower probability of opting out of the emission-rate standards applied to all combustion plants operating before 1987.[4] I seek to go beyond the analysis found in Meyer and Pac (2017) and analyze the LCP directive comprehensively. In this paper, I pay critical attention to the performance of the oldest thermal combustion fleet (older than 1987) in the EU by comparing emissions concentrations of installations that opted-out to those that chose to comply with performance standards. I further explore that whether the LCPD created a perverse incentive for older stations to continue highly polluting operations without requiring performance standards. Those that opted out of the emission rate standards and eventually shutdown by the end of 2015 were more likely to be coal and lignite power plants. More importantly, these plants were not more likely to shutdown (as intended by the Article 4(3) requirements) than similar plants that chose to comply. This gives us some evidence that the LCP directive gave rise to the "old-plant" effect, deferring dirty plant shutdowns or replacements.

In the next section, I briefly review some empirical literature concerning air quality control using emission-rate standards. The remainder of the paper is organized as follows: Section 2.3 provides a detailed description of the Large Combustion Plant Directive and other overlapping policies that were in force during the same regulation period. Section 3.3 describes the data from the EEA. Section 2.5 estimates the causal effect of emission standards under Articles 4(3) and 4(1), along with falsification tests. Section 2.6

[4] I have reason to be wary of this result: Considering that many of these combustion plants had multi-fuel input, I redo their analysis using plant-level input shares of fuel type (solid fuels, natural gas, liquid fuels, other gases, biomass) as predictor variables instead of absolute fuel inputs in petajoules. I find that relative to natural gas combustion, a higher share of coal, lignite, or liquid fuel was associated with an increased likelihood of being opted out of emission limits values - which is opposite of the result found in Meyer and Pac (2017). This may imply that some operators of coal and lignite plants found that returns to eventual shutdown by the end of 2015 were higher than investing in costly retrofits to comply with the emission limits values in the LCPD.

investigates the policy impact of tighter standards under Article 4(2) taking potential anticipation effects seriously in the identification strategy. In Section 3.7, I conduct more robustness checks. Section 2.8 investigates whether the old opt-out combustion plants were more likely to close than plants under different regulation regimes. Lastly, Section 3.11 concludes.

2.2 Related Literature

In the last two decades, there has been a notable increase in research evaluating policies for environmental protection. The design of empirical studies emphasizes causal inference by comparing a group of regulated (treated) firms with a comparable (control) group of firms that were not subject to the treatment. As a result, we now have an improved perspective on the causal effects of environmental regulations that target industrial pollution. The literature evaluating the effectiveness of emission performance standards in non-EU countries, notably the United States, has been extensive.

A large majority of these studies use the spatial variation in the implementation of the US Clean Air Act (CAA) to evaluate the effect of air quality regulation under the CAA framework. As a result, many regulation categories of the Clean Air Act have come under empirical evaluation. Greenstone (2004) shows that by the end of 1970s most of the US counties were in compliance with the National Ambient Air Quality Standards (NAAQS) for SO_2 concentrations. But the author finds that whether a county came under SO_2 regulation (nonattainment status) under the Clean Air Act did not play a major role in the improvement of ambient air quality for sulfur dioxide. While Chay and Greenstone (2003) demonstrate that total suspended particles (TSPs) pollution fell dramatically in the early 1970s and that these large changes in ambient TSPs concentrations were regulation induced. Henderson (1996) documents that nonattainment counties successfully reduced ozone concentrations relative to attainment counties. Nevertheless, the regulation may have had unintended and costly consequences due the non-uniform implementation of the environmental regulation across the US. Becker and Henderson (2000) and Henderson (1996) find evidence of a reduction in the number of polluting plants in regulated counties and a shift over time of industrial plants to unregulated counties. That is, the industries affected by the regulation slowly relocated their activities to areas that were less polluted (attainment counties) and therefore evaded regulation requirements to install the cleanest available technology.

Harrison et al. (2015) investigate the effectiveness of the Indian Supreme Court Action Plans (SCAP) and price incentives via fuel taxes to reduce coal use and promote SO_2 pollution abatement technology. Using a comprehensive industrial plant-level dataset, they find that higher coal prices led to a significant reduction in coal use as an input into production across plants. However, they further find that the SCAP were only successful in targeting large highly polluting installations. Greenstone and Hanna (2014) use city-level data to evaluate the impact of the SCAP and the Mandated Catalytic Converters. They provide evidence that air pollution regulation resulted in observable improvements in air quality. Another recent paper looks at the extent to which Chinese power plants react to tighter SO_2 emission-rate standards and find that the response to the regulation was swift, with average SO_2 stack concentrations (in mg per Nm^3) falling by 13.9% (Karplus et al., 2018).

Wätzold (2004) assesses the success of the highly ambitious SO_2 emissions limits (for both new and existing large combustion plants) of the Ordinance on Large Combustion Plants in 1983 (GFA-VO) in Germany[5]. Along with the regulatory provisions of the GFA-VO, the government of North Rhein Westfalen (NRW, the largest German state) was able to negotiate a voluntary agreement with the electricity suppliers in NRW to limit SO_2 and NOx emissions from new and existing plants. Wätzold documents that these policy initiatives led to the installation of flue-gas desulfurization (FGD) technology in the entire fleet of combustion plants regulated in Germany. That, is the policy was successful in the quick and uniform diffusion of state-of-the-art abatement technology.

For the purposes of policy design, if the emission-rate or technology standards for regulated pollutants only apply to new rather than existing polluting sources, there is a concern that such a policy-exemption rule, often referred to as "grandfathering", could encourage the operation of plants that are older and dirtier over the longer run. One such policy is the New Source Performance Standards (NSPS) introduced under the 1970 Clean Air Act in the US. The NSPS featured emission-based standards for only new sources and mandated up to a 90% reduction in SO2 emissions from earlier pre-regulated levels. Empirical studies validate that the mandated investment in scrubbers increased operation costs of new plants, which led the operators to utilize older unregulated plants at higher capacity (Stavins, 2006), and delayed re-investment in existing plants to avoid triggering the Clean Air Act requirements (Bushnell and Wolfram, 2012). Although the LCP directive did not require stringent desulfurization or denitrification from the (older) existing polluting plants, it did nevertheless impose either lenient standards on the stack concentrations or limited operations. I will investigate the effectiveness of this specific design feature of the LCP directive in this paper.

[5]The GFA-VO and a comparable program in Netherlands (Dutch Bees WLV 1987) are considered to be model initiatives for the LCP directive.

2.3 Policy Context

2.3.1 Large Combustion Plant Directive

The LCP directive was first adopted by the European Council in 1988[6], subsequently amended in 1994[7], and then revised on the 23th October of 2001[8]. While the structure of regulation has more or less remained the same since initial implementation, the performance standards are stricter with each revision. The directive specifies upper limits for the emission intensity of SO2, NOx and particulate matter (dust) that each regulated combustion plant could emit on average each year. Until January 2005, installations had to comply with the 1988 directive, while the 2001 Large Combustion Plant Directive kicked into effect starting January 2008 and its validity ended on 31st December 2015.

Figure 2.1 is a pictorial description of regulatory provisions under the LCP directive. A plant that could prove that the construction licence was granted before 27.11.2002 and that the plant went into operation before 27.11.2003 is referred to as an "old-new" plant and was subject to provisions under article 4(1) of the directive. Plants that came into operation after 27.11.2003 are referred to as "new-new" plants, subject to provisions under article 4(2) of the directive, and exposed to significantly more stringent regulations than the "old-new" plants or "existing" plants. Significant emission reductions were required from "existing plants" that were licensed before 1 July 1987 via either the national emission reduction plan (NERP) or meeting the emission limit values set for "old-new" plants under article 4(1). Existing power stations (older than 1987) could "opt-in" and be subject to lenient emission standards or "opt-out" and instead reduce their operation hours and eventually shutdown by 2015.[9] In the analysis that follows, I seek to quantify the impact of emission rules on polluting behavior at the stack/plant level.

Tables 2.1 to 2.3 summarize the performance standards stated as emission limit values for SO_2, NOx, and particulates that were set to be achieved by January of 2008. The regulation intensity for each controlled pollutants varied depending on whether the plant would be eventually subject to article 4(1) or article 4(2) of the directive. As evident from the tables, new combustion plants regulated under article 4(2) have considerably

[6]Directive on limitation of emissions of certain pollutants in to the air from large combustion plants, 88/609/EEC, Official Journal L336, 7.12.1988.

[7]Amending Directive 88/609/EEC on the limitation of emissions of certain pollutants into the air from large combustion plants, 94/66/EC, Official Journal L337, 24.12.1994.

[8]Directive on limitation of emissions of certain pollutants in to the air from large combustion plants, 94/66/EC, Official Journal L309, 27.11.2001.

[9]Note that there were comparable national programs (e.g. GFA-VO 1983 in Germany, and Dutch Bees WLV 1987 in Netherlands) in place, before the EU level LCP directive. I do not expect these older policies to bias the results as I have no reason to believe that they affect article 4-1 and article 4-1 plants differentially post-2007.

tighter emission limit values (stricter compliance standards) than do older plants under article 4(1). Moreover, these performance standards varied by the type of fuel input (e.g. solid, liquid, or gaseous) and capacity of the plant as measured by thermal megawatt (MWth) input.

It is important to note that the directive applied not only to the electricity and heating sectors, but all thermal generation from large combustion units, irrespective of the sector. This included, as a result, firms in the iron, steel, paper, sugar, chemicals, and rubber sectors generating power and heat onsite.

2.3.2 Potential Compliance Mechanisms

To comply with the directive, plant operators have a number of compliance options. In order to reduce emissions intensity, there could be (1) a change in the fuel-mix used, e.g. increase the share of emission compliant fuels like natural gas, (2) installing and using pollutant abatement technology - e.g. retrofitting the plant with scrubber technology designed for each pollutant type to clean the flue gases, (3) increases in operational or fuel efficiency, (4) closure of non-compliant units or a change in the merit order (e.g. temporary production status or peak-use only). In the analysis, I find some evidence on what share of the compliance mechanism for old plants could be attributed to fuel-switching.

2.3.3 NEC targets & 2008

During the same (observable) regulation period, the European Parliament set national emission ceilings (NEC) for absolute emissions in kilotonnes for sulphur dioxide, nitrogen oxides, volatile organic compounds and ammonia for each of 15 EU member states[10]. These targets were to be achieved between 1990 and 2010. However, these emissions targets were not sector-specific: that is, they could have been achieved cumulatively by reductions in the transport, agriculture, waste, commercial, energy production, and industrial sectors.

The analysis in this paper focuses only on the energy production and distribution sector, so it is likely that the threat to identification due to the NEC targets is low. Nevertheless, the reader may have residual concern that the NEC targets could bias the estimates for the LCP directive. This may be true if I have reason to believe that the NEC targets affected plants regulated under Articles 4(1) and 4(2) differentially. Similarly, NEC targets are a concern if opt-out plants reacted differently from plants that chose to comply with

[10]Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, and the U.K.

ELVs. I will seek to explain the impact of the LCP directive on stack-level emissions concentrations rather than absolute emissions, so NEC targets should not be a concern.

Figure 2.2 shows that absolute emissions from the energy production and distribution sector fell at a much higher rate in 2008 and 2009, likely due to the great recession. It is all the more important therefore to focus the analysis on emissions intensity rather than absolute emissions to correctly estimate the impact of the LCP directive. To allay still any residual concerns, I will impose country-specific fixed effects on emissions intensity to capture possible confounding effects of the NEC regulation targets and year-specific fixed effects to pick up time-specific unobservable shocks that were common at all power stations.

2.3.4 EU ETS

Generally, threats to identification exist if an event or unobservable factor affect emission concentrations from plants in the selected treatment and controls groups in a systematically different way and I am unable to control for it. Take for example the EU ETS: all thermal combustion plants regulated as a large combustion plant (of at least 50 MWth capacity) under the directive were also regulated under the EU ETS, covering all installations generating electricity larger than 20 MWth. Presumably, all large combustion plants considered in this paper received free emission allowances in the first two trading periods, resulting in low compliance costs under the EU ETS.

Despite the ensuing low carbon-price environment, the carbon market could potentially bias treatment estimates if the significant over-allocation of allowances distorted incentives to abate co-pollutants regulated under the LCPD. Free allowances were based on estimates of historical carbon emissions, which are strongly correlated with the size of each installation or plant. To address any bias due to interactions with the EU ETS, I condition on the size of the plant (MWth) in all specifications. Notwithstanding, both treatment and control groups were subject to the EU ETS and the effect (if any) should be differenced out in the empirical strategy.

Since the carbon trading market would most affect power generators using carbon-intensive fuels, I further show that the treatment effects are largely driven by combustion plants *without* any coal or lignite in the fuel mix in pre-treatment years. This an important result and should reassure the reader about the identification strategy – the EU ETS is unlikely to confound the estimated effects of the LCP directive.

2.3.5 IPPC Directive

The IPPC directive (Directive 96/61/EC of 24 September 1996) is a major threat to identifying the response of new plants to lower pollutant limits values or stricter emission standards at the stack-level. This is because the IPPC directive required operating permits in compliance with best available techniques, including the standards in the LCP directive, for all new plants or those undergoing major changes starting 30 October 1999.

I therefore have strong reason to expect that the policy interaction between the LCP and IPPC directives made it harder to avoid compliance with emission performance standards under Article 4(1) or Article 4(2) for plants with operation dates starting 1999. I am still interested in quantifying the effect of more stringent environmental standards under Article 4(2) and will take anticipation into account in the research design.

Note that IPPC was not a requirement for units that started operating pre-1987 and therefore older plants had no incentive to comply pre-deadline of 2008. Moving forward, the Industrial Emissions Directive integrates the LCPD and the IPPC, along with other directives, in one comprehensive regulation.

2.4 Data

The data on all large combustion activities come from the European Environment Agency (EEA), which had started an inventory of reported emissions from large combustion plants starting in 2004[11]. This database covers all plants with a rated thermal input of at least 50 MW operating in the European Union, covering 27 countries in 2004 and reaching 29 countries by 2015. For each plant, the database reports detailed information on operations including capacity, energy input, fuel input by type, emissions of local pollutants, date plant started operations, and regulation status under the LCPD, including whether the plant opted-out or was part of the NERP. In addition, the inventory also collects plant identifiers (e.g. name, parent company, location, address) and also classifies the industrial sector in which the plant operates[12]. There are six industry classifications provided: Electricity Supply Industry, Combined Heat and Power, District Heating, Iron and Steel, Refineries, and Other (Paper, Sugar, Chemicals, Rubber, etc). See Table 2.6 for the industries covered.

[11]The databases were retrieved from one common public source, the EEA. Updated and improved versions were published as new data from regulated countries became available, checks for inconsistencies performed, and corrections were made (EEA 2016, EEA 2018a, and EEA 2018b).

[12]In the raw data there were many plants unidentified in terms of industry. I used reported information online from the the European Pollutant Release and Transfer Register (E-PRTR) to improve the precision and coverage of the industry classification. There remain still combustion units for which the industrial sector in unknown.

The status of the plant under the LCP directive is central to the assessment of whether a combustion plant is in compliance with the regulation. However, Germany and Sweden do not report the regulation status of their combustion plants to the EEA. To circumvent this lack of information, I impute the regulation status using the start date of operation. Still, the information on the start date of operation is unavailable for all plants in the sample, and therefore I am unable to use all available data for Germany and Sweden in the estimations. Table 2.4 shows the breakdown of the number of plants by regulation status in each EU country, including where unknown.

Note that there were no combustion units that opted-out of emission-rate standards from Austria, Czech Republic, Germany, Denmark, Hungary, Croatia, Kosovo, Ireland, Lithuania, Latvia, Netherlands, and Sweden. Due to lack of control plants, I exclude these countries from the estimation sample when exploring the impact of emission standards on units regulated under Articles 4-3 and 4-1. Table 2.5 shows the breakdown of plants by regulation status for each member state with at least one opt-out combustion plant.

2.4.1 From Absolute Emissions to Emissions Intensity

The LCP regulation expresses the emission limit values in milligrams per cubic meter (mg per Nm^3). Since the EEA only provides absolute emissions of NOx, SO_2, and particulate matter, as reported by the plants, I convert tonnes emissions into flow rates (mg per Nm^3). For the dependent variable, I combine information on raw fuel usage (in petajoules) with tonnes emissions to construct the outcome variable of interest, emissions intensity. To do this I need estimates of the flue rates associated with specific fuel types. I start with using flue rates assumptions provided in the study by Wynn et al. (2017). I check whether the estimates are sensitive to assumptions involved in the calculation of the flue rates and this is not the case. I also conduct sensitivity analysis by defining emissions intensity as emissions divided by total fuel input - the results are strongly robust to this and quantitative conclusions remain the same.

2.4.2 Historic Trends in Emissions Intensity

Figure 2.3 graphs the emissions intensity grouped by concentration intensity from very high to low for all large combustion plants reported in the EEA database. Emissions intensity of regulated pollutants were on a declining trend - the combustion activities are cleaner in 2015 as compared to 2004. But I can also see that emission intensities have not come down much further since 2012. The darkest grey area represents the share of total capacity (measured by summing all plant-level MWth) that emitted pollutant concentrations above the tightest standards for solid fuels in Article 4(2). The graphs show that close to a quarter of the system in 2015 was still emitting concentrations of regulated local pollutants that are likely to not comply with even tighter standards in the future (under the Industrial Emissions Directive).

The emission concentrations follow similar trends for NOx, SO_2, and dust, including the noticeable drop post-2007, same as the policy deadline for the LCP directive. Based on such observations of trends, it is hard to know the cause of the correlated declines in these key air pollutants concentrations.

2.4.3 Pre-treatment Statistics

Table 2.7 shows pre-treatment differences in means for the key variables between those plants that opted-out versus those that chose to comply with emission limits under Article 4-3. and Article 4-1. The table suggests that on average opt-out plants were much larger in size (as measured by MWth), used boilers to combust, and used more solid fuels (excluding biomass) and liquid fuels as a share of the total energy input. On the other hand, plants that chose to comply with the emission limit values were on average using more gaseous fuels and biomass as a share of total energy input, and used gas turbine as combustion type.

I will control for the size of the plant and construct emission intensity using information on specific-fuel input and their associated flue rates. Using emissions intensity in mg/nM^3 as the dependent variable will allow us to capture the differences in the fuel mixes. Fuel-switching is one of the mechanisms using which plants seek to comply with emission-performance standards. For this reason, I want to avoid controlling for time-varying plant-level fuel input such as fuel type shares to avoid post-treatment bias. Nevertheless, controlling for fuel input shares could inform us about how much of the compliance mechanism adopted by plants was due to fuel-switching.

Table 2.8 presents pre-treatment differences in means for the key variables between plants regulated under Article 4(1) Article 4(2). The variables shown appear to be similar in distribution. Moreover, pre-treatment differences of these key variables are relatively stable across years as well (not shown here).

2.5 Emissions Control Under Articles 4(3) and 4(1)

2.5.1 Research Design

In an ideal research setting I would have that the policy treatment was randomly assigned to plants such that regulatory status was independent of all possible factors affecting plant-level emissions - this is not the case. Moreover, I do not have emissions data on plants that were not regulated under the directive, i.e. all combustion plants with a capacity less than 50MWth.

To construct plausible counterfactuals, I look in the implementation details of the regulation across the set of plants under regulation. I take advantage of the variation across the three vintage-differentiated regulatory arms of the directive to assess the impact of emission performance standards. To investigate the effect of EPS on EU combustion plants (extensive margin), I use a difference-in-differences (DiD) framework. I treat plants that opted-out as the control group and plants that chose to meet the emission-rates under Article 4-3 and Article 4-1 as the treatment groups.

Note that the EPS under Article 4(3) are identical to those under Article 4(1). The only difference is that Article 4(3) plants are older and could choose not to come under performance standards - which were mandatory for Article 4(1) plants. The opt-out decision is indeed endogenous and likely correlated with a plant's emission trajectories. Using the difference in difference framework, I seek to control with this endogeneity concern. Moreover, this is likely not a serious problem given that emissions from opt-out plants were monitored throughout – they were allowed to opt-out from pollution abatement under the condition that emissions do not rise. To the extent that there may be differences in monitoring and enforcement across industries and countries, I control for this in the preferred specification.

The base specification is a DiD equation, which uses the reported emissions before the policy deadline (2004 to 2007) for pre-treatment data. Preferred estimation equation is the following:

$$y_{pt} = \alpha_p + \eta_t + \beta_0 \, D_{pt} + \theta_{ct} + \boldsymbol{\gamma} \cdot \mathbf{X}_{pt} + \phi_{it} + \boldsymbol{\lambda}_{rc} \cdot (\delta_{rc} \times t) + \epsilon_{pt} \tag{2.1}$$

where I expect the regulation to be in effect during the period from 2008 to 2015 for units subject to Articles 4(3) and 4(1). y_{pt} is the log of emissions intensity at plant p in year t. β captures the regulatory effect on emission concentrations at the stack level. All time-invariant confounders that capture plant-level features such as plant vintage and fuel-related combustion technology are captured by the plant-level fixed effects α_p. η_t absorbs year-specific shocks that are common across plants. θ_{ct} and ϕ_{it} are country-year and industry-year fixed effects respectively to control for time-varying unobservables. $\mathbf{X}_{pt}$ includes time-varying control for plant size or capacity (GWth).

To account for the considerable heterogeneity (unevenness) in the implementation of the LCPD policy across countries (for example, compliance stringency was left to the member states), I use regulation-specific linear trends ($\delta_{rc} \times t$) that are allowed to vary by country. This is in addition to the country-specific fixed effects to allow for time-varying differences in the policy environments across countries. Note that I do not control for fuel-type shares in my preferred specification, because it would lead to post-treatment estimation bias. This is because fuel-switching (e.g. substituting natural gas for other fossil-fuels, particularly coal) is an important option for thermal operators to meet the requirements of the LCP directive.

2.5.2 Identifying Assumptions

Here I will address the main identifying assumptions. Due to the fixed effects, the identification in the core empirical model comes from within-plant variation. For difference-in-differences specifications, I require that the Stable Unit Treatment Value Assumption (SUTVA) is met: that the treatment status of a regulated unit p does not impact the outcome of units other than p. Although it is in the operator's interest to minimize cost of operations, SUTVA could be violated if the parent company that owns multiple combustion units chooses to retrofit all plants irrespective of regulation status[13]. The potential biases due to such regulation spillovers can be signed. Namely, I provide lower-bounds of the true impact of EPS under the LCP directive.

It is absolutely necessary that the control and treated groups have common trends in emissions intensity, before the policy deadline. For us to interpret β as the causal effect of emission performance standards, I require that the emissions intensity outcomes of treated plants would have followed identical trends to those of the control plants in absence of treatment. It is not possible to test this directly, but I provide graphs and placebo tests to show that this condition is satisfied. Figure 2.4 demonstrates a favorable pictures for pre-treatment trends in outcomes for opt-out plants versus those that chose lenient emission limit values under Article 4(3) and Article 4(1). Note that these graphs are limited to those member states that had opt-out plants.

2.5.3 Results - EPS for Article 4(3) Plants

I estimate the effect of emission-rate standards under Article 4(3) in Tables 2.9 to 2.11. For identification I limit the sample to countries that had at any opt-out plants - I call them opt-out member states. These are 17 EU countries, with a total of 241 plants opting out of emission standards (see Table 2.5). I also exclude plants that were using a gas or diesel engine because the LCP directive did not apply to them.

[13] I am unable to test the strength of SUTVA by comparing the performance of thermal plants that are owned by the same firm, but are under different regulation regimes.

Table 2.9 quantifies the average impact of ELV on emission-intensity of NOx at the plant level. Column (1) is the simplest model, including only the interaction term of interest (Post 2007)*(4-3 ELV), time and plant fixed effects, and size control using plant capacity in GWth. Column (2) introduces industry by year fixed effects to capture any developments that may be unique to the industry. From Columns (3) and (4), I can see that the estimates for NOx are sensitive to the inclusion of any country-related fixed effects or trends. This is not as apparent in Tables 2.10 and 2.11, where I run the same models for SO_2 and particulate matter. Columns (4) shows estimates of equation 2.1, which is the preferred specification, and further controls for regulation-specific linear trends that are common to each member state. In Table 2.9, I see a negative change in NOx emission concentrations of about 11%, but the estimate is significant only at the 10% significance level.

To allay concerns that the differences in the distribution of covariates concerning fuel usage are driving the results, I add fuel controls in Column 5. The difference in the estimates from Columns 4 to 5 provide some indication of the importance of fuel-switching for older plants due to the emission-rate standards. In Table 2.9, after controlling for fuel input shares in Column 5, the coefficient on 4(3) ELV treatment is four percentage points (or 38%) lower than in Column 4. And this estimate is no longer statistically significant - suggesting that fuel-switching was on average a strong compliance mechanism for NOx abatement, than say retrofitting.

In Tables 2.10 and 2.11, I find that emission rate standards prompted plants under Article 4-3 to reduce SO_2 emission concentrations by close to 39% and dust concentrations by 26% relative to opt-out plants. Moreover, based on the differences between Columns 4 and 5, I can attribute about 30% of the reductions in SO_2 concentrations and about 25% of the reductions in dust concentrations to fuel-switching.

2.5.4 Effect Heterogeneity

In this subsection, I examine the heterogeneity in the causal impact. Specifically, I show how the effect on emission concentrations varied with the size of the combustion plant and whether the plant used any coal or lignite.

Combustion plants can be divided in size categories in terms of installed capacity: small (less than 100 MWth), medium (101-300 MWth), large (301-500), and very large (larger than 500 MWth). Along with fixed effects for capacity categories, I add additional interaction terms to capture treatment effect differentials by size of combustion plant. Table 2.12 shows convincingly that the large and very large combustion plants were most responsive to the emission performance standards. Interestingly, we also estimates significant declines in SO_2 concentrations for small- and medium-sized combustion plants. These results are consistent with the fact that relatively larger plants, using dirtier fuels in the total fuel-mix, faced stricter emission performance standards (see Tables 2.1, 2.2, and 2.3).

To give a visual representation of the strongest effects, Figure 2.6 shows the temporal disaggregation of the heterogeneity in treatment effects. Taken together, the graphs show that the effect of the directive started in 2008 and was not transitory or limited to specific years after the regulation went into effect. More crucially, the graphs provide strong evidence that the directive was particularly effective for the subgroups of plants that are most responsible for air pollution – very large combustion plants that dominate with high levels of installed capacity.

I further investigate any heterogeneity in the effect of EPS on the subgroup of combustion plants that had any coal or lignite in the total fuel-mix in the pre-treatment years of 2004 to 2007. Table 2.13 shows the results. Interestingly, I find strong evidence that the response of coal power stations was muted, in comparison with combustion plants using other fuel types.

2.5.5 Falsification Test

To conduct falsification tests, I use years 2006 and 2007 as hypothetical policy deadlines for compliance to the LCP directive. I do not expect anticipation to play any significant role for old plants complying with the emission standards: (1) because of high costs for plant operators to retrofit older plants or enhance operational efficiency, and (2) because IPPC was not a requirement for combustion units that started operating pre-1999 and therefore majority of older plants had no incentive to comply before the 2008 compliance deadline.

Since all plants regulated under Article 4(3) and most under Article did not have any other regulatory requirements (e.g. in the IPPC directive), I assume away the possibility of detecting anticipation prior to 2008. I consider therefore this to be a strong test for common trends, in addition to the visual checks in Figure 2.4. I stick to the preferred specification in equation 2.1 - the inclusion of fuel controls do not change the result - and the results are presented in Table 2.14.

As expected, the estimated effects on plant-level emission concentrations before the compliance deadline of 2008, for all three pollutants, are statistically insignificant. On the other hand, estimates in the second row could be an indication that the response was already taking effect after 2006 - inconclusive, however.

2.5.6 Results - EPS for Article 4(1) Plants

I conduct the identical exercise to estimate the effect of emission-rate standards under Article 4(1) in Table 2.15. Again, for identification I have limited the sample to opt-out member states only. I find that combustion units regulated under Article 4(1) were prompted to reduce SO_2 emission intensity by 31% under the lenient performance standards. For the other two pollutants under consideration, the effect was statistically insignificant.

In contrast to the observed response by Article 4(3) seen in Tables 2.10 and 2.11 suggests that the emission limits values under Article 4(1) were perhaps too lenient. This is not surprising as I see in the right column of Figure 2.4, the combustion units were on average already relatively clean in 2004. Imposing the same emission performance standards for Article 4(3) and 4(1) plants seems to have fallen short of environmental progress on emissions abatement.

Tables 2.14 and 2.15 give us assurance that the post-2007 treatment effects observed are prompted by the emission performance standards under Articles 4(3) and 4(1), rather than something else unobserved.

2.6 Emissions Control Under Article 4(2)

2.6.1 Research Design

Now I turn to estimating the effect of tighter emission limits imposed under the LCP directive. I would like to identify the effect of tighter standards on new plants from the change in emission intensities of Article 4(2) units compared with the change in emission intensities of Article 4(1) units. I am unable to exploit the D-I-D framework applied thus far because I expect anticipation to play a role for the following reasons:

- Plants getting operation permits after the LCP directive was announced in 2001 would be already aware of the emission standards required. If plant operators have prior access to information on future compliance requirements and are reasonably forward-looking - I expect them to invest early.
- New plants, as opposed to old existing plants, using newer combustion technology would find it relatively cheaper to invest early (possibly also costly to delay).
- As discussed in Section 2.3.5, the IPPC directive required new units and those undergoing "substantial changes" to meet technology standards starting 30 October 1999. I expect therefore plants starting operations after 1998 to be more forward-

looking (less myopic) in adhering to EPS requirements.

Figure 2.5 shows that the requirement of common trends does not hold because trends in emissions intensity of article 4(1) plants differ significantly from that of article 4(2) plants during the pre-treatment period, most notably for NOx. In light of the policy interaction between IPPC and LCP directives, I find it difficult to rule out anticipation as one of the explanations for the significant declines in emission intensities of NOx and SO_2 by all plants affected by IPPC before the LCPD deadline - see the right column of Figure 2.2.

To circumvent the problem of anticipation, I do the following:

- I assume that the regulation assignment rule was arbitrary (plants staring operation after 2002 came under Article 4(2)) and that it was difficult for operators to "game the system" or to expedite the issuance process of an operation permit. Given this assumption, the regulation status for plants just before and after 2003 is as good as random. Therefore, plants near the cutoff date are similar in unobservable characteristics that affect emission concentrations at the stack-level. The closer to the cutoff date, the stronger my identification assumption - although not rigorously testable in this study. Nonetheless, I will control for all possible observable time-varying plant-level characteristics and also impose combustion type fixed effects.

- I do not impose any policy deadline for compliance with emission standards in this setting. I compare the performance of the treated versus control plants during the full observed period from 2004 to 2015.

I estimate the following equation for plants near the cutoff date of 2003:

$$y_{pt} = \alpha_0 + \beta \mathrm{S}_p + \boldsymbol{\gamma} \cdot \mathbf{X}_{pt} + \lambda_m + \theta_{ct} + \phi_{it} + \epsilon_{pt} \tag{2.2}$$

where y_{pt} is the log emission intensity of pollutant of interest. $S_p = 1$ indicates whether the plant came under stringent EPS under Article 4(2). The base category is EPS under Article 4(1). $\mathbf{X}_{pt}$ captures plant-level operations such as fuel input shares by fuel type and plant capacity in GWth. η_m are fixed effects for combustion type. θ_{ct} and ϕ_{it} country and industry fixed effects allowed to vary by year.

2.6.2 Results

Tables 2.16, 2.17, and 2.18 estimate equation 2.2 for emission intensities of NOx, ceSO2, and dust respectively. I use plants that started operations either 2003 and 2004 as the treated group. Columns (1) and (2) use all plants that started operations 1999 to 2002 as the control group, while Columns (3) and (4) limits the control group further to only those with 2000 and 2001 as operation start-dates.

Relative to emission limits values under 4(1), stricter emission performance standards caused average NOx concentrations to drop further between 7-16%, SO_2 concentrations to fall by 27-28%, and dust concentrations by 30-40%. These results are robust to re-defining emission intensity as kilotonnes of emissions per petajoule of input do not change the results.

2.7 Further Robustness Checks

Here I address the possibility that results discussed in the previous sections are due to another factor that I may have not considered.

2.7.1 Alternative Treatment and Control Groups

It is important to show that the results are robust to alternative treatment and control groups. The reader might be worried that it is simply that newer plants are cleaner than the older ones - that a remaining confounding factor might be newer technology. I expect that plant vintage or time-invariant fuel-technology should be captured by the plant-fixed effects and time variables already. Nevertheless, I rerun the estimations using Article 4-1 as the treatment regulation, and for the control group I use Article 4-3 plants that chose to comply with Article 4-1 standards. Both groups were subject to identical emission limit values. Then the difference between these two groups should not be the regulation, but rather improvements in technology over time. Once I control for plant-fixed effects, I do not expect to find Article 4(1) plants to respond on average more than those under Article 4(3) - especially since Article 4(1) plants were already on average cleaner than the older plants. Table 2.19 confirms this and demonstrates that there are no significant differences in emission intensities of local pollutants between the treatment and control groups. These results provide further assurance that I am correctly attributing the effects I find to emission performance standards under the LCP directive.

2.8 Shutdown of Grandfathered Plants

In this section I will explore whether the old and dirty opt-out plants were "grandfathered" under the LCP directive. Under Article 4(3), opt-out plants avoided environmental standards, but were supposed to limit operating hours to 20,000 and close by the end of 2015. Did this happen?

Table 2.20 shows that a large share of the 241 opt-out plants did not actually close down by the initial required date of 2015. I still observed 60% of the combustion units operating in 2016. More interestingly, I observe that plants which were subject to emission-rate standards were shutting down in large numbers during the same period. About 82 combustion units under Article 4(3) that chose to comply with emission standards were closed by the end of 2007. Generally, I observe a high number of Article 4(3) ELV plants closing operations in the LCPD policy-active period.

A natural question arises: did the LCP directive indeed promise the closure of opt-out plants or did it offer non-compliant plants a perverse incentive to continue dirty operations relative to those complying with ELV? I investigate the determinants of the (endogenous) shutdown decision using the full EEA dataset in a linear probability model:

$$\text{shutdown}_{pt} = \alpha_0 + \alpha_3 4(3)_p + \alpha_1 4(1)_p + \alpha_2 4(2)_p + \boldsymbol{\gamma}_{\mathbf{X}} \cdot \mathbf{X}_{pt} + \lambda_m + \theta_{ct} + \phi_{it} + \epsilon_{pt} \quad (2.3)$$

where $4(3)_p = 1$, $4(1)_p = 1$, and $4(2)_p = 1$ indicate that the combustion unit was subject to EPS under Articles 4(3), 4(1), and 4(2) respectively. Here the base category is opt-out status under Article 4(3). $\mathbf{X}_{pt}$ capture a host of plant-level operations and outcomes such as fuel input shares by fuel type, emissions intensities of NOx, SO_2, particulate matter, whether the plant was part of NERP, and plant capacity in GWth and absolute energy input in petajoules. η_m are fixed effects for combustion type. θ_{ct} and ϕ_{it} country and industry fixed effects allowed to vary by year. $shutdown_{pt}$ is a binary (0 or 1) dependent variable indicating whether the plant closed at the end of the reporting year. I assume that the plant was shutdown if I do not observe it the next reporting year.

I estimate this linear probability model by ordinary least squares in Table 2.21 for both the full sample and then again limiting the estimation sample to only opt-out member states. The results reveal that opt-out plants were more likely to shutdown during the policy period than newer combustion plants complying to emission rate standards under Article 4(1) and 4(2). But surprisingly opt-out plants did not close more often than those of similar age under Article 4(3). Given the estimates are stable across the two samples, I have confidence about the robustness of the qualitative findings. I find evidence in this section that the LCP directive "grandfathered" the oldest and dirtiest power stations and allowed them to keep running over the long run.

2.9 Conclusion

Effective pollution control in the complex regulatory context of the European Union is an important policy objective. The Large Combustion Plant Directive was a major EU environmental policy. This paper offers the first impact assessment of this policy and uses micro data for the full population of regulated large combustion plants to estimate causal changes in emissions intensity at the plant-level. I evaluate whether the policy instrument succeeded in pollution control by the oldest thermal power generators and whether stricter emission standards were a significant catalyst for improved environmental performance.

I use combustion plants that opted-out of lenient emission limit values as the counterfactual and demonstrate that older units under Article 4-3 (licensed before 1987) complying with emission performance standards responded with significantly cleaner emission concentrations post compliance-deadline. The results are strongest for SO_2 and total PM concentrations, but also hold for NOx for larger combustion plants. Moreover, emission performance standards imposed on newer units (under Article 4-1, licensed after 1987 and before 2002) did not react as much as older units - most likely, because the standards imposed were too lenient.

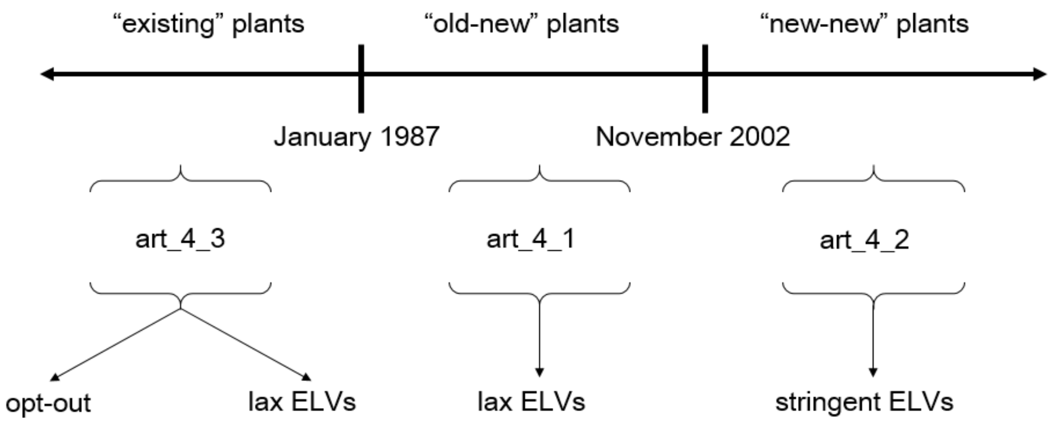
Given the policy interaction between the LCP directive and the IPPC directive, which required new units and those undergoing "substantial changes" to meet technology standards starting 30 October 1999, I have strong priors that combustion plants with operation permits starting 1999 were not as myopic in complying with the directive. To evaluate the effect of tighter emission performance standards under Article 4-2 on new plants I take this policy interaction between the LCP and IPPC directives and limit the estimation sample to those combustion plants that started operation after 1998. Then I measure the change in emissions intensity of new plants licensed just after 2002 relative to those licensed just before 2002 - allowing us to estimate the local treatment effect near the applicable cut-off date for tighter emission limits values. The result indicate that tighter standards applied to new plants had an economically meaningful impact on all measures of local pollutant emission concentrations.

The results are robust to a range of specifications and falsification tests, so that I can be confident that I am accurately attributing the findings to variations in emission limits values under the Large Combustion Plant directive. Taken together, evidence from this empirical study suggests that EU-wide emission performance standards, when sufficiently stringent, are an effective instrument for pollution abatement at the plant stack-level. Whether the LCP directive, written as a vintage-differentiated regulation, created a perverse incentive for older power stations to continue highly polluting operations remains an empirical question, however.

A uniform policy with respect to plant vintage is more likely to encourage investment by incumbents towards cleaner equipment earlier in the regulation period. The "grandfathering" convention was partially present in the LCP directive, because it allowed a large share of older installations to continue operations without requiring stringent emission-rate standards. Although politically more feasible, this had the potential to worsens pollution over the longer-run by encouraging the operation of power stations that are older and dirtier. Those that opted out of emission rate standards and eventually shutdown by the end of 2015 were more likely to be coal and lignite power plants. Furthermore, these plants were not more likely to shutdown (as intended by the Article 4(3) requirements) than similar plants that chose to comply with standards. This gives us some evidence that the LCP directive gave rise to the "old-plant" effect, deferring plant shutdowns or replacements that would otherwise be important for environment protection. Crucially, positive emissions during the increased lifespan of these older plants may have more than offset the increase in pollution abatement from plants complying with emission performance standards.

Given that I find that plants under Article 4(1) did not respond significantly to the Large Combustion Plant Directive, future research should investigate whether the additional requirements and more stringent standards under the Industrial Emissions Directive encouraged these existing plants to reduce emissions concentrations further or shutdown. To maximize pollution abatement, limits on emission intensities should be uniformly applied and sufficiently stringent for all regulated units to protect public health and the environment.

Figure 2.1: Licensing Date and Plant Status under the LCP Directive

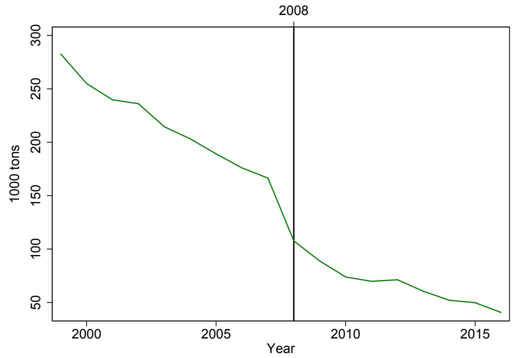


Notes: Own illustration.

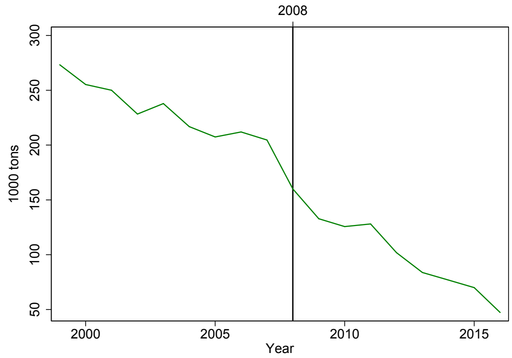
Figure 2.2: Trends in Absolute Emissions by EU Region

(a) NOx emissions in Western EU

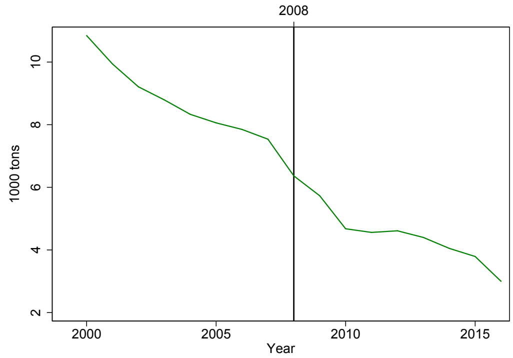
(b) NOx emissions in Eastern EU



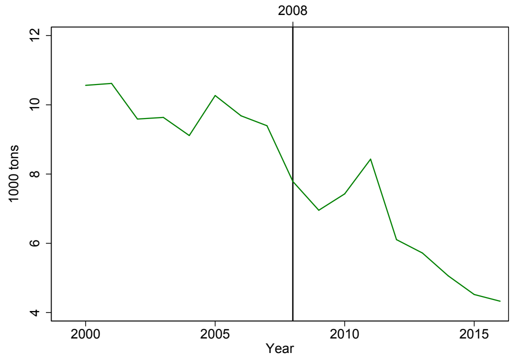
(c) SO2 emissions in Western EU



(d) SO2 emissions in Eastern EU



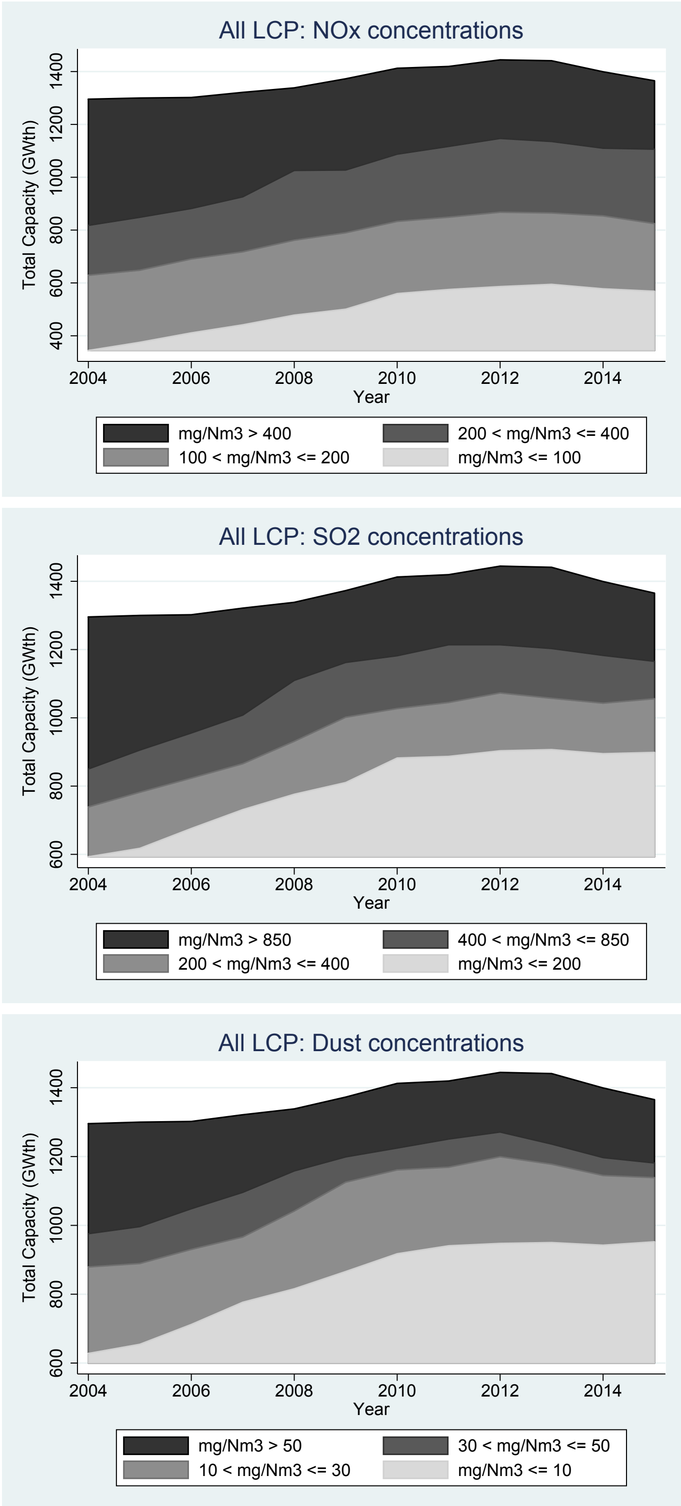
(e) PM10 emissions in Western EU



(f) PM10 emissions in Eastern EU

Notes: Data come from the air emission inventories (EEA, Eurostat), which provides annual data on air pollutants by source sector. The figures plot the trends in absolute emissions from the energy production and distribution sector. Eastern EU region consists of Romania, Czech Republic, Hungary, Lithuania, Poland, Slovakia, Slovenia, Bulgaria, Cyprus, Estonia, Malta, Latvia. Western EU region consists of the remaining 16 EU countries. The vertical black line is to mark year 2008.

Figure 2.3: Pollution Intensities from EU's Thermal Combustion Plants



Notes: The graphs show the emissions intensity grouped by concentration intensity from very high to low for all EU large combustion plants reported in the EEA database.

Table 2.1: Emission Limit Values for SO_2 by Regulation Status under LCPD

	Size of the Plant (MWth)					
	50 - 100		100 - 300		> 300	
Under article	**4(1)**	**4(2)**	**4(1)**	**4(2)**	**4(1)**	**4(2)**
Solid Fuels	2000	850	2000 to 400 (linear decline)	200	400	200
Liquid Fuels	1700	850	1700 to 400 (linear decline)	400 to 200 (linear decline)	400	200
Biomass	n.a.	200	n.a.	200	n.a.	200
Gaseous Fuels in general	35	35	35	35	35	35
Liquefied Gas	5	5	5	5	5	5
Low calorific gas from coke oven	800	400	800	400	800	400
Low calorific gas from blast furnace	800	200	800	200	800	200

Notes: The emission limit values are expressed in milligrams per normal cubic meter (mg/Nm^3).

Table 2.2: Emission Limit Values for NOx by Regulation Status under LCPD

Under article 4(1)	Size of the Plant (MWth) 50 - 500	> 500
Solid Fuels	600	500
Liquid Fuels	450	400
Gaseous Fuels in general	300	200

Under article 4(2)	Size of the Plant (MWth) 50 - 100	100 - 300	> 300
Solid Fuels	400	300	200
Liquid Fuels	400	200	200
Natural gas	150	150	100
Other gas	200	200	200
Biomass	400	300	200

Notes: The emission limit values are expressed in milligrams per normal cubic meter (mg/Nm^3).

Table 2.3: Emission Limit Values for Particle Dust by Regulation Status under LCPD

Under article 4(1)	Size of the Plant (MWth) < 500	≥ 500
Solid Fuels	100	50
Liquid Fuels	50	50
Gaseous Fuels		
general rule	5	
blast furnace gas	10	
gases produced by steel industry	50	

Under article 4(2)	Size of the Plant (MWth) 50 to 100	> 100
Solid Fuels	50	30
Liquid Fuels	50	30
Gaseous Fuels		
general rule	5	
blast furnace gas	10	
gases produced by steel industry	30	

Notes: The emission limit values are expressed in milligrams per normal cubic meter (mg/Nm^3).

Table 2.4: Regulation Status by All Member States

	4-3 Opt out	4-3 ELV	4-1 ELV	4-2 ELV	Unknown	Total
Austria	0	58	42	29	28	157
Belgium	3	72	35	33	4	147
Bulgaria	3	27	0	1	3	34
Cyprus	7	4	11	3	0	25
Czech Republic	0	93	26	3	7	129
Germany	0	315	197	59	228	797
Denmark	2	59	53	17	21	152
Estonia	3	12	1	8	2	26
Spain	23	73	30	129	4	259
Finland	23	106	61	44	9	243
France	29	134	85	54	53	355
Greece	4	34	15	27	0	80
Croatia	0	15	3	2	0	20
Hungary	0	31	11	19	9	70
Ireland	0	17	10	8	3	38
Italy	20	176	178	156	66	596
Lithuania	0	29	3	3	12	47
Luxembourg	0	0	1	0	0	1
Latvia	0	23	1	13	6	43
Malta	4	0	6	1	0	11
Netherlands	0	106	81	45	36	268
Poland	39	50	10	12	26	137
Portugal	6	9	13	20	2	50
Romania	41	116	13	15	8	193
Sweden	0	76	21	8	129	234
Slovenia	5	9	2	3	0	19
Slovakia	11	40	26	14	0	91
United Kingdom	18	207	182	60	27	494
Kosovo	0	5	0	0	0	5
Total	241	1896	1117	786	683	4721

Notes: The table shows the number of plants regulated under each regulation arm of the LCPD.

Table 2.5: Regulation Status by Opt-Out Member States

	4-3 Opt out	4-3 ELV	4-1 ELV	4-2 ELV	Closed by 2015
Belgium	3	72	35	33	3
Bulgaria	3	27	0	1	1
Cyprus	7	4	11	3	1
Denmark	2	59	53	17	1
Estonia	3	12	1	8	2
Spain	23	73	30	129	0
Finland	23	106	61	44	21
France	29	134	85	54	11
Greece	4	34	15	27	0
Italy	20	176	178	156	14
Malta	4	0	6	1	4
Poland	39	50	10	12	7
Portugal	6	9	13	20	6
Romania	41	116	13	15	0
Slovenia	5	9	2	3	0
Slovakia	11	40	26	14	8
United Kingdom	18	207	182	60	16
Total	241	1128	721	597	95

Notes: The table shows the number of plants under each status category. The last column identifies the number of opt-out plants that shutdown by 2015. I assume that plant operations were closed, if I do not observe the plant in 2016.

Table 2.6: Distribution of EU Combustion Plants by Industry

Industry	# of Plants
CHP	811
District Heating	461
Electricity Supply	1354
Iron/Steel	62
Other (Paper, Sugar, Rubber, Chemicals)	928
Refineries	116
Other Unknown	387
Total	4040

Notes: The table shows the number of plants observed in each industrial sector from 2004 to 2015, provided the regulation status is known.

Table 2.7: Summary Statistics of Key Plant Features - Opt Out MS

	Regulation Status											
	Article 4(3) - Opt out				**Article 4(3) - ELV**				**Article 4(1) - ELV**			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Size (MWth)	719.87	1140.92	50	7889	465.36	938.55	0	12600	328.99	471.14	0	5500
Energy Input (pt)	7.14	14.40	0	122.71	6.53	17.56	0	280.97	5.58	9.61	0	92.69
Solid Fuel %	41.66	47.07	0	100	25.14	41.25	0	100	10.83	29.13	0	100
Liquid Fuel %	34.16	44.88	0	100	23.65	36.15	0	100	12.65	29.93	0	100
Natural Gas %	20.62	37.20	0	100	35.28	44.41	0	100	62.83	46.47	0	100
Other Gases %	3.07	15.10	0	100	13.51	28.93	0	100	8.87	25.93	0	100
Biomass %	0.50	2.78	0	30.56	2.43	12.78	0	99.86	4.83	18.80	0	100
Boiler	0.78	0.42	0	1	0.64	0.48	0	1	0.37	0.48	0	1
Gas Turbine	0.03	0.17	0	1	0.10	0.31	0	1	0.51	0.50	0	1

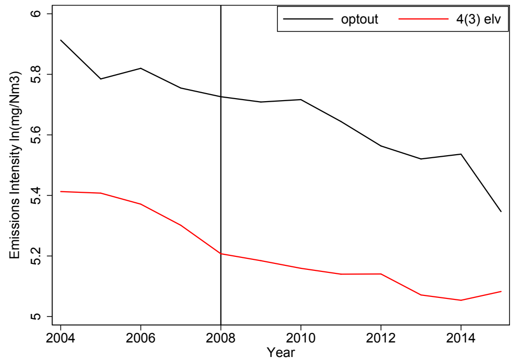
Notes: The table reports average values from pre-treatment years (2004 - 2007) and the sample is limited to opt-out member states.

Table 2.8: Summary Statistics of Key Plant Features - All EU28

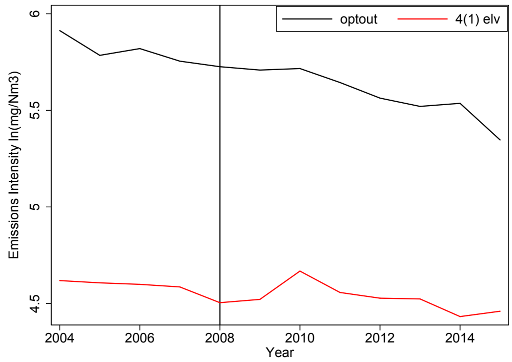
	Regulation Status							
	Article 4(1) - ELV				**Article 4(2) - ELV**			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Size (MWth)	324.71	486.09	0	5500	391.95	369.12	0	2400
Energy Input (pt)	5.26	9.76	0	121.25	5.52	6.63	0	38.99
Solid Fuel %	12.53	31.43	0	100	5.90	20.79	0	100
Liquid Fuel %	10.94	28.27	0	100	10.91	29.28	0	100
Natural Gas %	61.08	46.83	0	100	71.27	43.80	0	100
Other Gases %	11.24	29.67	0	100	5.42	21.10	0	100
Biomass %	4.20	17.84	0	100	6.50	21.82	0	100
Boiler	0.45	0.50	0	1	0.33	0.47	0	1
Gas Turbine	0.45	0.50	0	1	0.57	0.50	0	1

Notes: The table reports average values from pre-treatment years (2004 - 2007).

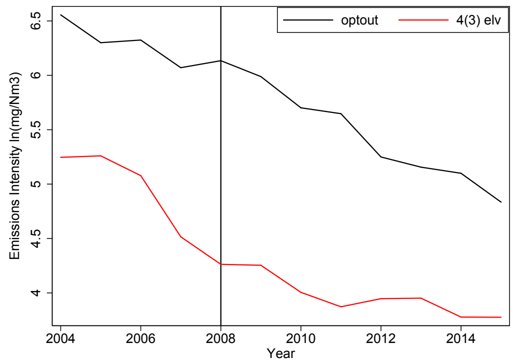
Figure 2.4: Diagnosis of Trends I



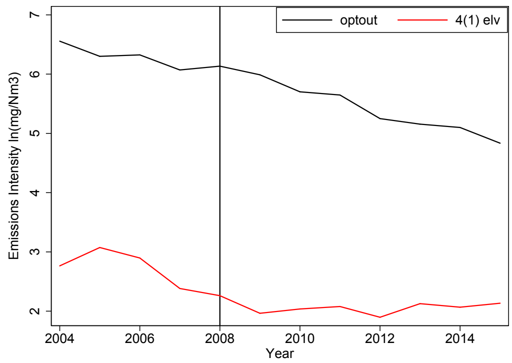
(a) NOx - Opt Out MS



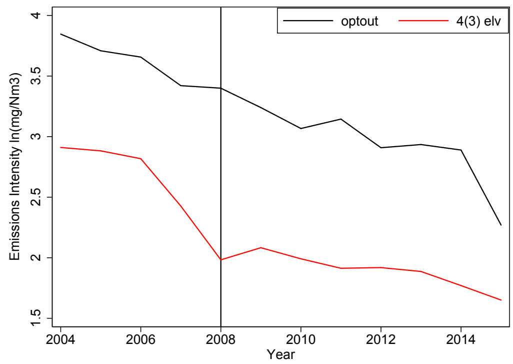
(b) NOx - Opt Out MS



(c) SO2 - Opt Out MS



(d) SO2 - Opt Out MS

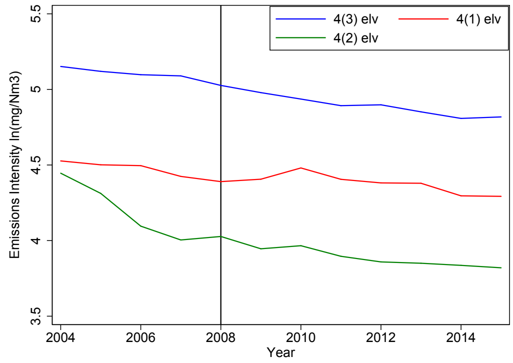


(e) Dust - Opt Out MS

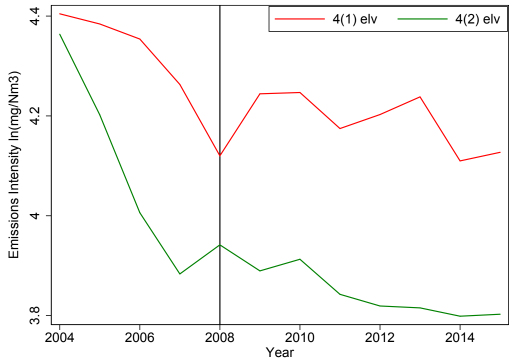
(f) Dust - Opt Out MS

Notes: The LHS column plots the trends in emission intensities from Article 4(3) plants against opt-out combustion plants. The RHS column plots the trends in emission intensities from Article 4(1) plants against opt-out combustion plants. The samples are limited to those countries with opt-out combustion plants.

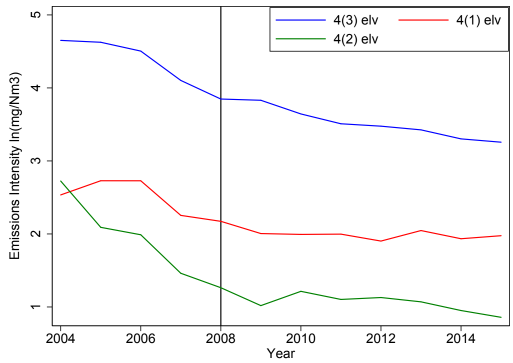
Figure 2.5: Diagnosis of Trends II



(a) NOx - All LCP

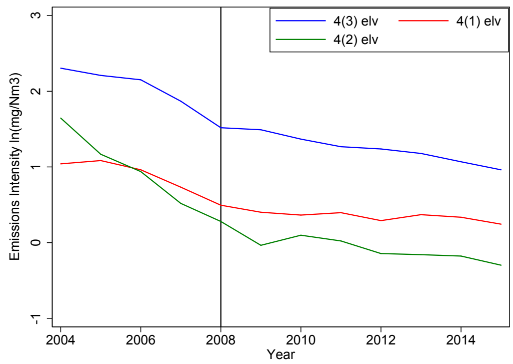


(b) NOx - Affected by IPPC



(c) SO2 - All LCP

(d) SO2 - Affected by IPPC



(e) Dust - All LCP

(f) Dust - Affected by IPPC

Notes: The RHS column plots emission intensities for all plants that starting operating after 1998. The RHS sample gets limited to those combustion units for which I have information on the operation date. LHS plots the trends for all large combustion plants in the full database and reveal similar trend differences between 4(1) ELV and 4(2) ELV plants.

Table 2.9: Effect on NOx of EPS Under Article 4(3) Regulation

	Dependent variable: ln (NOx)				
	(1)	(2)	(3)	(4)	(5)
(Post 2007)*(4-3 ELVs)	-0.110***	-0.105***	-0.072	-0.105*	-0.065
	(0.041)	(0.042)	(0.045)	(0.058)	(0.052)
Size Control	Yes	Yes	Yes	Yes	Yes
Fuel Control					Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes
Industry-by-Year FE		Yes	Yes	Yes	Yes
Country-by-Year FE			Yes	Yes	Yes
Regulation-Country Specific Trend				Yes	Yes
N	11,361	11,361	11,361	11,361	11,361
R^2	0.7636	0.7664	0.7764	0.7774	0.8193

Notes: The dependent variable is the log of emissions intensity (mg/nM^3). I use the date of starting operation to impute the regulation status of DE and SE combustion plants. The sample is limited to EU countries with opt-out plants under Article 4(3). Combustion plants that were licensed post-January 1987 are not included in the analysis. I also exclude plants that were using a gas or diesel engine. Size control is the size of the plant in GWth. Fuel controls include the fuel input share of solid, biomass, liquid, other gases, and natural gas (%). The total number of clusters/plants used in estimation were 1283. Standard errors in parentheses are clustered at the plant level for all regressions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.10: Effect on SO_2 of EPS Under Article 4(3) Regulation

	Dependent variable: ln (SO_2)				
	(1)	(2)	(3)	(4)	(5)
(Post 2007)*(4-3 ELV)	-0.270**	-0.289**	-0.218*	-0.394***	-0.276***
	(0.113)	(0.117)	(0.122)	(0.104)	(0.083)
Size Control	Yes	Yes	Yes	Yes	Yes
Fuel Control					Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes
Industry-by-Year FE		Yes	Yes	Yes	Yes
Country-by-Year FE			Yes	Yes	Yes
Regulation-Country Specific Trend				Yes	Yes
N	9,765	9,765	9,765	9,765	9,765
R^2	0.8606	0.8642	0.8725	0.8737	0.9140

Notes: The dependent variable is the log of emissions intensity (mg/nM^3). I use the date of starting operation to impute the regulation status of DE and SE combustion plants. The sample is limited to EU countries with opt-out plants under Article 4(3). Combustion plants that were licensed post-January 1987 are not included in the analysis. I also exclude plants that were using a gas or diesel engine. Size control is the size of the plant in GWth. Fuel controls include the fuel input share of solid, biomass, liquid, other gases, and natural gas (%). The total number of clusters/plants used in estimation were 1170. Standard errors in parentheses are clustered at the plant level for all regressions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.11: Effect on Dust of EPS Under Article 4(3) Regulation

	Dependent variable: ln (Dust)				
	(1)	(2)	(3)	(4)	(5)
(Post 2007)*(4-3 ELV)	-0.319***	-0.258***	-0.240***	-0.256**	-0.192**
	(0.087)	(0.088)	(0.086)	(0.103)	(0.089)
Size Control	Yes	Yes	Yes	Yes	Yes
Fuel Control					Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes
Industry-by-Year FE		Yes	Yes	Yes	Yes
Country-by-Year FE			Yes	Yes	Yes
Regulation-Country Specific Trend				Yes	Yes
N	9,274	9,274	9,274	9,274	9,274
R^2	0.7945	0.7980	0.8104	0.8117	0.8481

Notes: The dependent variable is the log of emissions intensity (mg/nM^3). I use the date of starting operation to impute the regulation status of DE and SE combustion plants. The sample is limited to EU countries with opt-out plants under Article 4(3). Combustion plants that were licensed post-January 1987 are not included in the analysis. I also exclude plants that were using a gas or diesel engine. Size control is the size of the plant in GWth. Fuel controls include the fuel input share of solid, biomass, liquid, other gases, and natural gas (%). The total number of clusters/plants used in estimation were 1107. Standard errors in parentheses are clustered at the plant level for all regressions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.12: Heterogeneity by Size of Plant

	Dependent variable: ln (mg/nM^3)		
	NOx	SO_2	Dust
(Treatment)*(MWth< 100)	-0.0588	-0.362**	-0.102
	(0.0716)	(0.159)	(0.138)
(Treatment)*(100 ≤MWth< 300)	-0.0385	-0.342***	-0.150
	(0.0652)	(0.130)	(0.121)
(Treatment)*(300 ≤MWth< 500)	-0.124*	-0.473***	-0.261*
	(0.0729)	(0.163)	(0.138)
(Treatment)*(500 ≤MWth)	-0.173***	-0.390***	-0.371***
	(0.0639)	(0.130)	(0.120)
N	11,361	9,765	9,274
Adj R^2	0.746	0.853	0.782

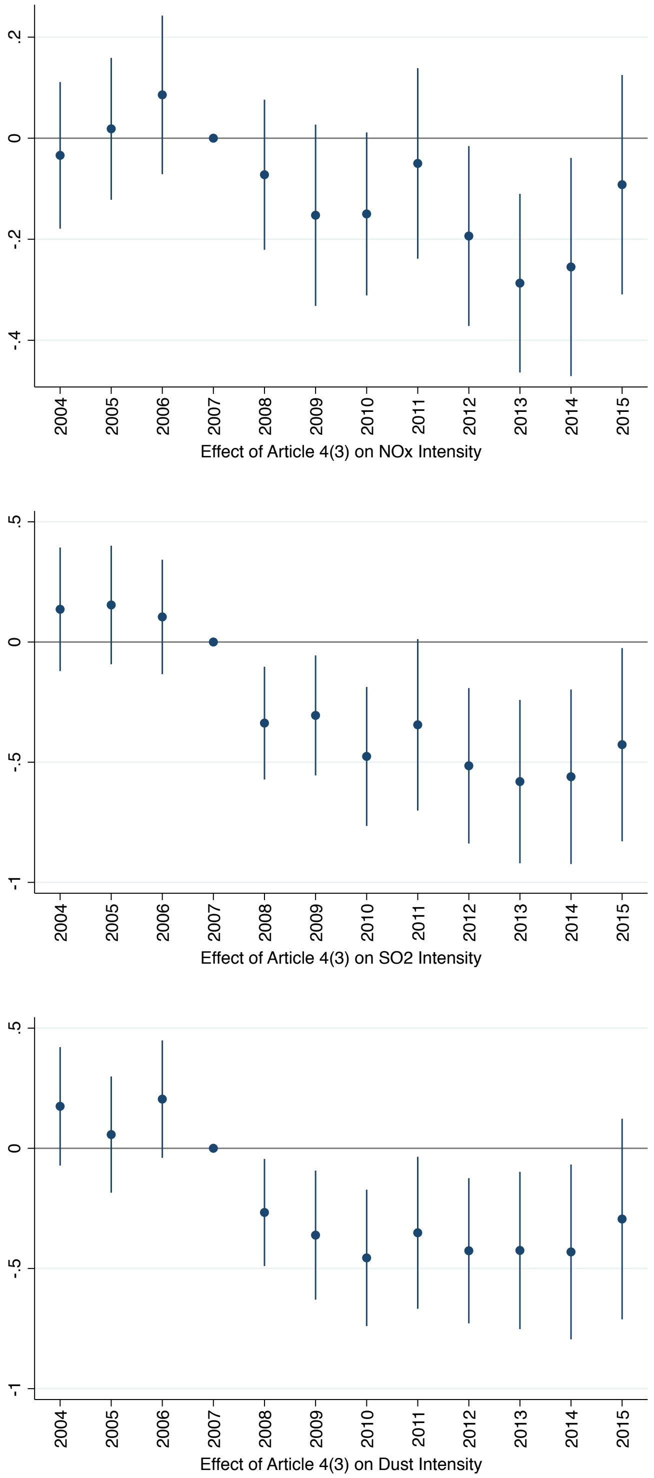
Notes: Table reports coefficients on the interaction terms with size capacity classes of combustion plants. The regressions include control for MWth, fixed effects for capacity class, plant, year, industry by year, country by year, and linear time trends for regulatory differences between countries. The dependent variable is the log of emissions intensity (mg/nM^3). The sample is limited to EU countries with opt-out plants under Article 4(3). Combustion plants that were licensed post-January 1987 are not included in the analysis. I exclude plants that were using a gas or diesel engine. Treatment is defined as (Post 2007)*(4-3 ELV). Standard errors in parentheses are clustered at the plant level for all regressions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.13: Coal Power Stations

	Dependent variable: ln (mg/nM^3)		
	NOx	SO_2	Dust
(Treatment)*(Other)	-0.0876	-0.632***	-0.314***
	(0.0583)	(0.129)	(0.120)
(Treatment)*(Solid Fuel)	-0.0992	-0.160	-0.204*
	(0.0631)	(0.117)	(0.112)
N	10,513	9,057	8,723
Adj R^2	0.754	0.853	0.784

Notes: Table reports coefficients on the interaction terms with an indicator for whether the observed combustion plant used any solid fuel (mainly coal) in the total fuel mix before 2008. The regressions include control for MWth, fixed effects for capacity class, plant, year, industry by year, country by year, and linear time trends for regulatory differences between countries. The dependent variable is the log of emissions intensity (mg/nM^3). The sample is limited to EU countries with opt-out plants under Article 4(3). Combustion plants that were licensed post-January 1987 are not included in the analysis. I exclude plants that were using a gas or diesel engine. Treatment is defined as (Post 2007)*(4-3 ELV). Standard errors in parentheses are clustered at the plant level for all regressions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2.6: Effect Heterogeneity: Size $\geq$ 300 MWth



Notes: In this figure, I disaggregate the ATT to shows how pollution concentrations of treated versus control combustion plants evolved for plants with thermal capacity greater than 300 MWth. 2007 is the reference year, the year before the LCPD went into effect. The dependent variable is the log of emissions intensity (mg/nM^3). All regressions included a control for MWth capacity and fixed effects for plant and year. 95% confidence intervals provided and standard errors were clustered at the plant level.

Table 2.14: Effects of EPS Under Article 4(3) Regulation - All Pollutants

	Dependent variable: ln (mg/nM^3)								
	NOx	SO_2	Dust	NOx	SO_2	Dust	NOx	SO_2	Dust
(Post 2007)*(4-3 ELV)	-0.105*	-0.394***	-0.256**						
	(0.058)	(0.104)	(0.103)						
(Post 2006)*(4-3 ELV)				-0.073	-0.133	-0.118			
				(0.061)	(0.115)	(0.110)			
(Post 2005)*(4-3 ELV)							-0.003	-0.032	0.022
							(0.046)	(0.104)	(0.100)
N	11,361	9,765	9,274	11,361	9,765	9,274	11,361	9,765	9,274
R^2	0.7774	0.8737	0.8117	0.7774	0.8735	0.8116	0.7773	0.0.8735	0.8116

Notes: The dependent variable is the log of emissions intensity (mg/nM^3). All regressions included a control of size and fixed effects for plant, year, industry-by-year, country-by-year, and regulation-by-country linear time trends. I use the date of starting operation to impute the regulation status of DE and SE combustion plants. The sample is limited to EU countries with opt-out plants under Article 4(3). Combustion plants that were licensed post-January 1987 are not included in the analysis. I exclude plants that were using a gas or diesel engine. Size control is the size of the plant in GWth. Fuel controls include the fuel input share of solid, biomass, liquid, other gases, and natural gas (%). Standard errors in parentheses are clustered at the plant level for all regressions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.15: Effects of EPS Under Article 4(1) Regulation - All Pollutants

	Dependent variable: ln (mg/nM^3)								
	NOx	SO_2	Dust	NOx	SO_2	Dust	NOx	SO_2	Dust
(Post 2007)*(4-1 ELV)	-0.045	-0.307**	-0.176						
	(0.068)	(0.124)	(0.126)						
(Post 2006)*(4-1 ELV)				-0.097	-0.197	0.026			
				(0.083)	(0.138)	(0.138)			
(Post 2005)*(4-1 ELV)							-0.045	-0.054	0.109
							(0.062)	(0.123)	(0.130)
N	8,196	5,932	5,545	8,196	5,932	5,545	8,196	5,932	5,545
R^2	0.7563	0.9058	0.8548	0.7564	0.9058	0.8547	0.7563	0.9058	0.8548

Notes: The dependent variable is the log of emissions intensity (mg/nM^3). All regressions included a control of size and fixed effects for plant, year, industry-by-year, country-by-year, and regulation-by-country linear time trends. I use the date of starting operation to impute the regulation status of DE and SE combustion plants. The sample is limited to EU countries with opt-out plants under Article 4(3). I exclude plants that were using a gas or diesel engine. Size control is the size of the plant in GWth. Fuel controls include the fuel input share of solid, biomass, liquid, other gases, and natural gas (%). Standard errors in parentheses are clustered at the plant level for all regressions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.16: Effect of Article 4(2) versus Article 4(1) Regulation on NOx Plants Affected by IPPC

	Dependent variable: ln (NOx)			
	(1)	(2)	(3)	(4)
	kt/pt	mg/nM^3	kt/pt	mg/nM^3
	1999-2004	1999-2004	2001-2004	2001-2004
4(2) ELV	-0.162***	-0.160***	-0.070*	-0.066
	(0.037)	(0.037)	(0.042)	(0.042)
Fuel Controls	Yes	Yes	Yes	Yes
Size Control	Yes	Yes	Yes	Yes
Combustion FE	Yes	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes	Yes
4(2) Treated Plants	130	130	130	130
4(1) Control Plants	240	240	103	103
No. of Clusters	213	213	177	177
N	3,525	3,525	2,183	2,183
R^2	0.3584	0.5482	0.4167	0.6295

Notes: The dependent variable is the log of emissions intensity, defined either as emissions per energy input unit (kilotonnes per petajoule) or mg/nM^3. I exclude plants that were using a gas or diesel engine. Size control is the size of the plant in GWth. Fuel controls include the fuel input share of solid, biomass, liquid, other gases, and natural gas (%). Combustion FE are capturing the type of combustion plant (boiler, gas turbine, furnace, etc). Standard errors in parentheses are clustered at the country-by-year level for all regressions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.17: Effect of Article 4(2) versus Article 4(1) Regulation on SO_2 Plants Affected by IPPC

	Dependent variable: ln (SO_2)			
	(1)	(2)	(3)	(4)
	kt/pt	mg/nM^3	kt/pt	mg/nM^3
	1999-2004	1999-2004	2001-2004	2001-2004
4(2) ELV	-0.276**	-0.273**	-0.284**	-0.278**
	(0.115)	(0.115)	(0.123)	(0.123)
Fuel Controls	Yes	Yes	Yes	Yes
Size Control	Yes	Yes	Yes	Yes
Combustion FE	Yes	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes	Yes
4(2) Treated Plants	104	104	104	104
4(1) Control Plants	204	204	88	88
No. of Clusters	201	201	144	144
N	2,412	2,412	1,489	1,489
R^2	0.6312	0.6906	0.5738	0.6474

Notes: The dependent variable is the log of emissions intensity, defined either as emissions per energy input unit (kilotonnes per petajoule) or mg/nM^3. I exclude plants that were using a gas or diesel engine. Size control is the size of the plant in GWth. Fuel controls include the fuel input share of solid, biomass, liquid, other gases, and natural gas (%). Combustion FE are capturing the type of combustion plant (boiler, gas turbine, furnace, etc). Standard errors in parentheses are clustered at the country-by-year level for all regressions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.18: Effect of Article 4(2) versus Article 4(1) Regulation on Dust Plants Affected by IPPC

	Dependent variable: ln (Dust)			
	(1)	(2)	(3)	(4)
	kt/pt	mg/nM^3	kt/pt	mg/nM^3
	1999-2004	1999-2004	2001-2004	2001-2004
4(2) ELV	-0.309***	-0.305***	-0.409***	-0.403***
	(0.107)	(0.106)	(0.110)	(0.109)
Fuel Controls	Yes	Yes	Yes	Yes
Size Control	Yes	Yes	Yes	Yes
Combustion FE	Yes	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes	Yes
Country x Year FE	Yes	Yes	Yes	Yes
4(2) Treated Plants	94	94	94	94
4(1) Control Plants	191	191	82	82
No. of Clusters	196	196	149	149
N	2,116	2,116	1,297	1,297
R^2	0.5127	0.6017	0.5157	0.6112

Notes: The dependent variable is the log of emissions intensity, defined either as emissions per energy input unit (kilotonnes per petajoule) or mg/nM^3. I exclude plants that were using a gas or diesel engine. Size control is the size of the plant in GWth. Fuel controls include the fuel input share of solid, biomass, liquid, other gases, and natural gas (%). Combustion FE are capturing the type of combustion plant (boiler, gas turbine, furnace, etc). Standard errors in parentheses are clustered at the country-by-year level for all regressions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.19: Alternative Treatment (Article 4-1) and Control Group (Article 4-3) Robustness Check

	Dependent variable: ln (mg/nM^3)					
	NOx		SO_2		Dust	
(Post 2007)*(ELV)	0.014 (0.034)	0.009 (0.033)	0.060 (0.077)	0.054 (0.069)	0.089 (0.072)	0.073 (0.069)
Size Control	Yes	Yes	Yes	Yes	Yes	Yes
Fuel Control		Yes		Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Regulation-Country Specific Trend	Yes	Yes	Yes	Yes	Yes	Yes
N	27,253	27,253	20,688	20,688	19,632	19,632
R^2	0.7326	0.7587	0.8835	0.9127	0.8313	0.8534

Notes: The dependent variable is the log of emissions intensity (mg/nM^3). I use the date of starting operation to impute the regulation status of DE and SE combustion plants. I exclude plants that were using a gas or diesel engine. Size control is the size of the plant in GWth. Fuel controls include the fuel input share of solid, biomass, liquid, other gases, and natural gas (%). Standard errors in parentheses are clustered at the plant level for all regressions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.20: Plant Shutdowns by Last Reporting Year

Shutdown Year	4(3) Optout	4(3) ELV	4(1) ELV	4(2) ELV
2004	0	4	0	0
2005	0	6	0	0
2006	0	5	0	0
2007	0	82	15	8
2008	3	44	22	21
2009	9	47	9	8
2010	3	34	9	2
2011	4	27	9	1
2012	10	59	32	14
2013	19	66	30	7
2014	11	45	15	8
2015	35	134	62	40
Total	95	553	203	109

Notes: The table shows the number of plant shutdowns by regulation status. I assume that plant was shutdown, if it was not reported to the EEA the next year.

Table 2.21: Were Opt-out Plants More Likely to Shutdown?

Linear Probability Model

	Dependent variable: Shutdown	
	(1) - All EU	(2) - Optout MS
Article 4(3)	-0.004	-0.004
	(0.003)	(0.003)
Article 4(1)	-0.010***	-0.009***
	(0.003)	(0.003)
Article 4(2)	-0.013***	-0.009**
	(0.004)	(0.004)
Opt Out	Omitted	Omitted
Fuel Controls	Yes	Yes
Emissions Intensity	Yes	Yes
NERP	Yes	Yes
Operation Controls	Yes	Yes
Combustion FE	Yes	Yes
Industry x Year FE	Yes	Yes
Country x Year FE	Yes	Yes
N	34,509	21,692
R^2	0.1860	0.2043
Clusters	3,973	2,624

Notes: This table reports estimates of Equation 2.2. The dependent variable is a binary variable (1 or 0) indicating whether the plant was closed by the end of the reporting year. I assume that plant was shutdown, if it was not reported to the EEA the next year. Operation controls consist of the size of the plant in GWth and absolute energy input in petajoules. Fuel controls include the fuel input share of solid, biomass, liquid, other gases, and natural gas (%). Emissions intensity controls for emission intensities of the three local pollutants considered in this paper. NERP is a dummy variable if the plant was part of the National Emission Reduction Plan. Combustion FE are capturing the type of combustion plant (boiler, gas turbine, furnace, etc). Standard errors in parentheses are clustered at the plant level for all regressions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Chapter 3

Inform Me When It Matters: Cost Salience, Energy Consumption, and Efficiency Investments

3.1 Introduction

Behavioural economic theory challenges standard assumptions that agents are fully attentive to information when making economic decisions (DellaVigna, 2009). For boundedly rational agents, the value of information may depend on when it is delivered to the decision maker. This is because the agent receiving the information has limited and varying degrees of attention – a scarce resource.

A number of studies confirm the theoretical prediction of consumer inattention – consumers react less to information that is relatively less salient. Effective attention to information may simply be a function of receiving timely information when making the consumption choices. Chetty et al. (2009) show using a field experiment that tax-inclusive prices at the grocery store induced a stronger behavioral response than sales tax added at the register. DellaVigna and Pollet (2009) find that investor response to information on stock earnings is stronger when the announcements are received during the weekday, when attention is more likely. Empirical work demonstrates that automated payment technology reduces price salience when agents do not need to view costs or prices, whether it is during payment of road tolls (Finkelstein, 2009) or monthly electricity bills (Sexton, 2015). Consumers become less price elastic or do not perceive the full cost of consumption, leading to an increase in consumption.

In the field of environmental economics, providing consumers real-time information on usage and prices has been shown to significantly reduce electricity and water demand (Jessoe and Rapson 2014, Pon 2017, Tiefenbeck et al. 2018). But does more frequent information have long-lasting effects and when or for whom is it more effective? Prest (2020) demonstrates using machine learning methods that consumer awareness is most predictive of heterogeneous demand response to time-of-use prices displayed on in-home monitors. In the intermittent billing context, Wichman (2017) evaluates the response of water use in response to an increase in the frequency of billing information (bi-monthly to monthly) and finds that the intervention was ineffectual for inattentive consumers. In contrast, more frequent billing improved the transparency of costs and increased consumption for large water users during the summer. Even with routine monthly billing for electricity consumption, Gilbert and Zivin (2014) show that households alter consumption behaviour significantly only in the first week after the bill arrives and that this response is stronger during the hotter months, when consumption is likely higher. These studies demonstrate that the effectiveness of information treatments is largely driven by high baseline users, during peak consumption periods, when usage costs are most salient.

Given that salience of information plays a prominent role in consumer attention to energy costs, I consider in this paper whether the timing of bills is a factor in determining heat energy demand by households. More specifically, I investigate the effect of (not) receiving billing information when it matters the most for heat energy demand – during the heating season. The delivery of heating bills in Germany is relatively unique compared to that in other countries. Households receive energy bills once a year, as opposed to quarterly or monthly, with information on annual usage, prices, and charges[1]. Moreover, the 12-month billing period varies from building to building – that is, the closing date for billing (meter reading date) is not always the end of December[2].

To my knowledge, this paper is the first in the literature to exploit the unique natural experiment in billing cycles to understand whether heat demand reacts to salience of information (consumption, costs of energy, and payment settlement) on energy bills. For households receiving heating bills during the summer or low usage months, misperceptions of the true cost of heating energy are likely to be higher when winter comes along and

[1]The consumer makes monthly advance payments (in equal installments, called “Abschlag”) towards the annual bill. At the end of the billing period, each consumer then receives an individualized-consumption bill (since 1981 due to the Heat Cost Ordinance), a summary invoice with the actual consumption and costs, along with the final sum to be refunded or due as payment after factoring in the advance payments.

[2]The beginning or the end of the billing period largely depends on the type of energy with which the billable building is heated. The distinction comes from whether the heating fuel is supplied directly by a utility company or bought by the owner of the building. Thus, the billing cycle of the building is determined by the purchase cycle of the owner (for oil, wood, pellets) or the supply cycle of the supplier (for natural gas or district heating). For a significant share of buildings the heating bills end during the summer months April to August.

these misperceptions are increasing with consumer inattention to untimely bills. In other words, salience of heating energy costs is arguably elevated during the winter months, when most of the heating consumption takes place[3]. In this setting, inattention arises simply because of the temporal distance between when heating costs are revealed and when heating is used. Moreover, this temporal distance is exogenous to the decision of households residing in a building – in terms of potential energy consumption outcomes.

I find new evidence for consumer inattention to energy bills and show that heat energy demand is sensitive to time-varying salience of heating costs. Compared to buildings with calendar year billing, I find that off-winter billing accounts cause residential buildings to consume on average up to 9 percent more heat energy every year from 2008 to 2018, a period of both increasing and decreasing, but relatively high fuel prices[4]. I provide evidence that over-consumption due to lack of salience of heating costs and bills is pervasive and applies to all building types and fuel sources. Moreover, these ATE estimates capture the long-term effects – lingering behavioral bias after learning and compensating adjustments have taken place on the part of consumers over time[5]. Most importantly, I show that salience bias is sensitive to the 3-month sum of heating degree days post-billing, suggesting that households are effectively adjusting consumption in the first three months of the year-long billing cycle.

Unlike space heating, energy for water heating is consumed year-round and thus should not be as sensitive to billing cycle treatments. I test the same mechanism on hot water use and find consistent results, offering an interesting insight. Households billed during the off-heating season cut back on water heating use to compensate for the lack of salience and inability to adjust annual energy consumed for space heating. This provides evidence that the results are driven by time-varying salience and consumer inattention to heating costs.

This study also contributes to the understanding of any distributional concerns due to consumer inattention to energy bills. I take advantage of regional inequality to explore heterogeneous impacts. It is perhaps ambiguous how the rate of overconsumption should vary with the socioeconomic status of households living in a given building[6]. I estimate

[3]The majority of the heating costs incurred by households in Germany are due to space heating, for which the demand is practically zero during the summer season. See Table 3.1 for information on the average temperature and heating degree days experienced each month of the year from 2003 to 2018.

[4]We expect households that are unable to react timely (during winter season) to billing information to be less affected in response to price declines. But heating fuel prices were relatively high for most of the sample time period. See Appendix: Figure 3.1.

[5]This is because the buildings in my sample do not change billing cycles, unless undergoing refurbishments or change heating fuel. This is apparent in the data as the buildings (about 5% of total) drop out from the panel, before I observe a change in the billing cycle. Results are robust to limiting the sample to buildings that do not switch billing cycles from 2008 to 2018.

[6]I expect tighter budgets should cause households to be, cetris paribus, more attentive to energy

average treatment effects by terciles of the unemployment rate distribution and find that the timing of bills is just as important, if not more, for energy consumption by households living in poorer socioeconomic zip codes.

Using complementary data on energy performance certificates for a subset of buildings, I further investigate the potential long-term impact of salience bias (higher heating expenditures) on thermal-efficiency investments by building owners. To this end, I find novel evidence that non-salience of costs not only affected short-run yearly consumption outcomes by residents, but also fed into long-run investment decisions by the landlord or owner of the building. Specifically, I argue that higher heating expenditures over time provided stronger financial incentives for buildings most prone to salience bias in consumption to renovate and improve the thermal-insulation features of buildings. This further implies that building owners were indeed paying attention to annual energy costs and potential returns to energy efficiency investments. These differences in efficiency investments across billing cycles highlight that, at least for multi-apartment buildings, owners of buildings did invest towards closing any perceived energy-efficiency gaps, which were driven by consumer misoptimization by tenants, treated with low salience of energy bills.

The rest of the paper explains the findings in much more detail. The next section briefly presents a simple model of cost-salience that would apply to the empirical setting. Section 3.3 describes the data used in this paper. Section 3.4 assesses whether the stratified treatment assignment is as good as random and informs the research design. Section 3.5 presents the main empirical methodology and results, while Section 3.6 considers heterogeneity in the ATE with respect to the unemployment rate. Section 3.7 presents a battery of additional tests to check the robustness of the identification strategy and results. Section 3.8 investigates whether salience bias in consumption had long-term effects on energy-efficiency investments by building owners. In Section 3.9, I adapt the empirical strategy to account for potential selection bias concerns when considering all fuel sources and building types. Sections 3.10 and 3.11 conclude.

3.2 Theory

Here I use the model described in Sexton (2015) to capture diminished salience of energy costs related to billing that takes place during the off-heating season.

Suppose individuals enjoy an energy-related activity M at home, which is produced using an energy good X and technology α, according to $m = \alpha x$. Let p be the exogenous price

costs and demonstrate better learning of price expectations and billing information – leading to lower estimates of overconsumption.

of good. Suppose further that individuals derive utility from consuming a numeraire good, L. An individual's utility function is quasi-linear $U(l,m) = l + \theta V(m)$ and θ represents a taste parameter and function V is a twice differentiable and strictly concave function.

Consumer inattention related to diminished salience features in the model by assuming that individuals receiving bills during the summer potentially misperceive costs and observe only $\delta \in (0,1]$ of the true price of energy X - that is, $\tilde{p} = \delta p$, where $\delta = 1$ indicates full attention.

We could also consider the receipt of a bill ("Abrechnung") as a "true cost shock" that makes the consumer more attentive and that the "true cost shock" is more salient during the winter when consumption takes place.

The perceived optimization problem is then

$$\max_x U(l,m) = l + \theta V(\alpha x) \tag{3.1}$$

subject to

$$I = l + \delta p x \tag{3.2}$$

Assuming an interior solution we have that

$$V'(m) = \frac{\delta p}{\theta \alpha} > 0 \tag{3.3}$$

The straightforward prediction, therefore, is that keeping technology, tastes, and prices constant, greater inattention or reduced salience of the true cost of energy causes above-optimal consumption levels.

3.3 Data

The analysis in this paper is based on data combined from three sources: (1) data on building-level heating bills and energy performance certificates from a leading energy-metering company, (2) weather station data from the German Weather Service (Deutscher Wetterdienst), and (3) socio-demographic data from RWI-GEO-GRID (Breidenbach and Eilers, 2018).

The primary data used in the analysis is based a large panel of building-level heating bills for 420,573 residential buildings (3,215,800 bills) in Germany, with 12-month billing cycles that start during January 2008 to June 2018[7]. 12-month billing means that all

[7]The data is confidential and was received as part of a partnership between DIW Berlin and ista Deutschland GmbH to produce the Heat Monitor (Singhal and Stede, 2019) at DIW Berlin.

heating bills are for either 365 or 366 days, but the billing start and end dates vary. The sample covers residential apartment buildings using all main fuel types, with 2 or more apartment units, with very good regional coverage – over 7000 postal codes in all sixteen states of Germany are represented. I observe a building on average 9 times and a maximum number of 11 times.

The billing dataset provides information on the actual units of energy consumed for space heating and water heating, along with yearly costs incurred. The billing data also contains important building characteristics that help determine the energy requirements of buildings: living space (in square meters), building size (in number of apartments), location, and heating fuel type. To complement this information, I further observe information provided on energy performance certificates (EPC) issued from 2008 to 2018 (for about 40% of the buildings), on energy performance scores, year of construction, and the year of construction or renovation of key building components such as the heating system, roof, top floor or loft ceiling, outer wall, windows, and basement ceiling. For an even smaller subgroup of buildings (about 15%), I further observe whether these key building components met thermal-efficiency standards regulated under the 1995 Thermal Insulation Ordinance (Wärmeschutzverordnung or WSVO 1995) at the time of certification.

The main dependent variable is calculated as the annual quantity of heating energy consumed in relation to the heated living space of a building. This took several steps: first, building-specific consumption values are limited to the amounts of energy used for heating space (excluding warm water). Second, the consumption value is multiplied by the heating value corresponding to the building's energy fuel type, giving us the absolute heating energy consumption in kilowatt-hours (kWh) for a building during the billing period. Lastly, I divide total kilowatt-hours consumed by the amount of heated living space in the building. The units for heat energy consumption are therefore, kilowatt-hours per square meter of heated living space per year (kWh/sqm).

I calculate heating costs used for the heating energy consumed by first deducting costs of heating water from the total energy costs reported in each bill. Then dividing total costs for space heating by the total kWh units of heat energy consumed in the building gives us the cost per kWh of heat energy billed.

I supplement the billing dataset with weather station data from the German meteorological service (Deutscher Wetterdienst). I find the nearest available weather station to 8303 geocoded zip codes of Germany, provided that there is not more than one consecutive daily observation record missing for mean temperature for each weather station from 2003 to 2019. For the few missing values, I impute using the average of mean temperatures recorded for the previous and next day. This procedure amounts to using daily mean temperatures from 204 weather stations scattered across Germany to calculate heating degree days corresponding to each billing month and cycle.

The socio-economic variables used in this paper are the unemployment rate and the purchasing power[8] per household computed using grid level (1x1 kilometer cells) data from RWI and microm (2020), aggregated to the zip code level and matched to the billing sample. Currently, this information is only available for 2005 and 2009 to 2017.

3.4 Billing Cycles – A Natural Experiment?

In this section, I explore whether the billing cycle assigned to a building is independent of residing households' consumption behaviour.

In general, the beginning or the end of the billing period depends on the type of energy with which the billable building is heated[9]. The distinction is due to the supply of heating fuel. Natural gas and district heating are supplied to the building directly through an energy supplier and thus the billing cycle is determined by the billing cycle of the supplier. On the other hand, non-wired supply of fuel types like oil, wood,and pellets are purchased by the owner of the building. Nevertheless, it may be plausible that households choose the main heating fuel source or energy provider based on which billing cycle they offer – although I lack even anecdotal evidence to support this source of selection bias.

Table 3.2 summarizes the share of buildings observed to have billing accounts that end during different months in 2008, in a data sample of over 250,000 buildings. With 59% of properties using high calorific natural gas fuel for heating, natural gas is the most common fuel type, and most of the bills are calendar year bills that start in January and end in December. This is also the case for properties supplied with district heating.

The column indicating "August to February" in Table 3.2 reports the share of buildings that were assigned to billing cycles that start billing during or the beginning of the heating season. This column shows that the large majority of the bills are settled during the heating season for all fuel types except heating oil. For properties using heating oil, the billing cycle depends on the purchase of the fuel, which happens often during the summer months. About 40% of the buildings receive their bills during or beginning of

[8]A measure of disposable income - "the variable purchasing power reflects the household income. It comprises information on labour supply, capital wealth, rental and leasing income minus taxes and social security contributions, including social transfers such as unemployment benefits, child-allowances and pensions." (Breidenbach and Eilers, 2018)

[9]This statement is based on an email exchange with the data provider. I show in the paper that the assignment of billing cycles is further correlated with building size. For natural gas buildings, newer buildings were more likely to have calendar year accounts.

the non-heating summer months. Moreover, about half of the buildings using heating oil are not on the calendar year billing cycle.

Although the billing cycle assigned to a building is largely a function of heating fuel type, it may still be correlated with the building attributes and demographic composition that affect energy consumption. Even though households do not choose the billing cycles and are also not able to manipulate the assignment over time, households do choose where to live. It may be that, for example:

- more energy-saving or poorer households choose to live in larger buildings (with more apartment units), and
- the energy-efficiency attributes of buildings differ by size of the building.

Similarly, more energy-consuming households might choose to live in neighborhoods or zip codes with more one-family or two-family homes and fewer multi-apartment buildings. For these reasons, it will be important to condition on residing within a particular locale (state or PLZ zip code) and building type. Conditional on the building size and residing in a particular locale, the assignment of the billing cycle is plausibly exogenous to household decisions or behaviour.

In Tables 3.3 to 3.5, I present the distribution of billing cycles by building size (up to 10 apartments) for properties fired with oil, natural gas, and district heating respectively. Table 3.3 shows that calendar year billing (accounts that end in December) increases significantly with building size, while the share of bills that end during April to June is relatively stable. Table 3.4 gives information for properties fired with natural gas fuel – the share of calendar year billing increases significantly with the billing size. Larger buildings are more likely to have annual billing cycles that end during December, but this is not the case of district heating properties as seen in Table 3.5. The share of summer accounts is actually increasing with building size, while the share of calendar year accounts stays constant. Generally, I find that the incidence of non-calendar year billing is not stable as a function of building size.

I focus the main analysis on properties using heating oil, because the share of summer billing accounts is significantly higher, irrespective of building size – minimizing selection bias concerns[10].

I test whether I observe (quasi-) random assignment on one of the main determinants

[10]In Section 3.9 I show that the results also hold for the other fuel types. In particular, I find that natural gas buildings with calendar year billing are newer and thus more energy-efficient. After I control for building-level thermal insulation standards, I confirm the results drawn from the sub-sample of heating oil buildings.

of heat energy consumption, price per unit of consumption (kWh) by heating energy type. Table 3.6 reports t-tests of differences in means using simple regressions with fixed effects for the starting year and building size. To check for differences in means by fuel type, I regress fuel price (euro cents per kWh) on the starting month of billing assigned for all buildings and also limit the sample to buildings with less than 11 apartments. The omitted month is January, the starting month for calendar year billing, the control group. The first row of coefficients reports the mean price per energy unit incurred by the buildings in the control group.

For each of the fuel type considered, I find statistically significant differences in the mean price of energy for the majority of billing account types in the treatment group, compared to prices faced by buildings on the calendar year cycle. However, the reported coefficients show that these differences are very small in magnitude. There does not seem to be any economically significant variation in prices across billing cycles. Given the large number of observations, it is perhaps not surprising that I am able to detect such small differences in average prices.

For the main analysis in the next section, I use properties that use oil as heating fuel. Table 3.7 presents mean values of variables of interest for all oil-fired properties. There are clear statistical differences in the building attributes measured by the number of apartments in column 4 and the size of apartments (average heated square meter living space) for other billing cycles. Buildings with calendar year billing (January start) are larger on average, with more than 7 apartments per building, compared to other billing cycles. I measure the outcome variable (heat energy demand) using kWh units demanded per heated square meter living space and estimate the salience effect within building size.

In the analysis that follows, I only consider heating bills measuring consumption for 365 or 366 days. I do not delete any observations that have missing values for any of the variables used in the analysis or remove outliers for consumption, prices, living space, or number of apartments. Nevertheless, repeating the empirical analysis after doing so does not change the results[11]. Moreover the analysis can be replicated using an older billing panel, spanning years 2003 to 2012[12].

[11] See Appendix: Figure 3.2 for a plot of the trimmed distribution of the dependent variable.

[12] Additional results are available by request.

3.5 Empirical Design

3.5.1 Model

The main empirical approach identifies the heat energy demand response of buildings that have summer billing accounts[13] versus buildings that are billed for the more common calendar year billing period ending in December. After conditioning for heating fuel type and building size, whether a building receives the summer billing account is seemingly random – I will put this to the test.

I use the following baseline regression to estimate the average treatment effect of summer billing on heat energy demand:

$$y_{it} = \alpha_0 + \alpha_1 \text{May}_{it} + \alpha_2 \text{June}_{it} + \alpha_3 \text{July}_{it} + \delta \text{price}_{it} + \gamma_{size} + \lambda_t + \epsilon_{it} \tag{3.4}$$

where y_{it} denotes natural log of annual energy units consumed (kWh) per sqm by building i during the billing periods that started in year t.

- $\text{May}_i = 1$, $\text{June}_i = 1$, and $\text{July}_i = 1$ indicate that that a building has a billing account that starts in May, June, or July respectively.
- price_{it} captures the fuel specific-price per kWh unit of energy consumed.
- γ_{size} captures the fixed effects for the size of buildings (number of living units or apartments)
- λ_t are fixed effects for the year in which billing starts and ϵ_{it} the error term, clustered at the building level.

To improve upon the baseline estimates, I will further include two weather covariates: (1) the sum heating degree days (HDD) experienced in each zip-code for the 12 months during each billing period, and (2) the number of heating degree days experienced in each zip code in the first three month of the billing period. I include the 12 month HDD as a control because, by design, heating bills from different billing cycles do not cover the exact same 12 months. Although heating bills from different billing cycles do not cover the exact same 12 months, the 12-month rolling sum does not vary significantly across billing cycles as compared to the 3-month rolling sum.

In the last two columns of Table 3.1, I show that the 12-month rolling sum of heating

[13] I focus on the consumption response of billing cycles that start during the specific months of May, June, and July because of the high incidence of billing during these months as shown in Table 3.3. The months in Table 3.3 correspond to the month in which billing ends. Thus, if the bill ends in April, the next bill for the same building starts in May.

degree days do not differ significantly across billing cycles, but half the share of the total 12-month sum is experienced in the first three months when billing starts in November, December, and January. More importantly, the share of annual heating degree days experienced in the first 3 months post-billing is close to zero for billing cycles that start in May, June, and July. For this reason, I also include the 3-month intensity of heating degrees days after the receipt of a bill as a covariate. This controls for the fact that the salience of costs may be lower (higher) if the three months following billing are particularly warm (cold) in a given year.

In a nutshell, I identify the salience effect of costs or bills on energy consumption by analysing differences in energy consumed per unit of space between buildings using oil as heating fuel that (naturally) received different billing cycle treatments.

3.5.2 Results

Results reported in Table 3.8 show the average response of heat energy consumption for oil-fired buildings treated with May to July billing accounts, relative to calendar year billing. All specifications include fixed effects for building size. Column 2 controls for the price of heat energy per kWh. Column 3 adds year fixed effects to control for any annual shocks to consumption that are common to all buildings. Column 4 adds the 12 month HDD weather covariate. Column 5 estimates the effect within the same building size in the same German state, while Column 6 adds differences in purchasing power per household at the zip-code level. The model in Column 7 estimates using zip-code level fixed effects and Column 8 adds the 12 month HDD covariate.

The estimated coefficients are consistently between 2 and 4 percent approximately and highly statistically significant. Table 3.9 repeats the exercise in Table 3.8, after limiting the sample to oil-fired buildings with up to 10 apartments. The magnitudes and the significance of the estimated average treatment effects appear to be stable, and thus not sensitive to the inclusion of larger buildings that are less common in the German population of buildings using heating oil. These findings already provide strong evidence that consumers billed during summer months over-consume energy, likely because of consumer inattention to heating costs.

3.5.3 What drives (in)attention?

I probe whether the degree of salience bias in consumption is sensitive to recorded heating degree days, which is a baseline measure of how much heat energy a building requires. In Table 3.10, I estimate how the salience effect varies with an increase of 100 heating degree days recorded in the starting first to six months of the billing cycle. The coefficients on the interaction terms are highly statistically significant in the first three columns, highlighting that the sum of heating degree days in the first three months matter the most. An increase of 100 heating degree days experienced in the first month, immediately after billing, causes the rate of over-consumption to fall by 1.8 percentage points. The coefficients on the interactions indicate that salience of bills improves with heating degree days, but at a rate that is highest in the first month and decreasing as time since billing elapses.

In Table 3.11, I disaggregate the interaction effect with the annual sum of heating degree days to show exactly how the salience of heating costs varies over the 12 month heating period. Coefficients on the first three interaction terms show that attention to the heating bill is effective in the first three months. In contrast, more heating needs after the third month of the billing cycle leads to more salience bias in energy consumption.

This section provides supporting evidence that (1) households are indeed more attentive to costs when heating needs increase, and (2) attention takes place in the first three months (of the billing cycle), after which salience of costs has faded significantly. This suggests further that to maximize energy-savings, calendar year billing may still be sub-optimal as the benchmark. Given that the heating season lasts longer than three months, households that are informed of energy expenses at least twice during the winter heating season may be comparatively better off.

3.5.4 Cost Salience

Why do billing cycles make such a significant difference to annual heat energy demand? Given that attention diminishes with time, the temporal gap between the receipt of the heating bill and the heating season would lead to insalience of energy costs. I ascertain that the results for all billing cycles are indeed consistent with this insight, particularly affecting those households billed during the summer.

I use the most conservative model in column 8 from Tables 3.8 and 3.9, and now include a dummy for each possible billing cycle observed in the sample. Table 3.12 shows in the first column that the estimated effects on energy consumption for buildings assigned to the peak summer months of May, June, and July billing accounts remain positive and statistically significant. Controlling for the three-month sum of heating degree days post-billing in the second column, the salience effects almost double in size to between 5 and 7 percent. Now above-optimal energy consumption is not only limited to summer months of May to July. Relative to the calendar year billing period, buildings that are billed during the spring and autumn months of April, August, and September, also consume on average significantly more than those with calendar year billing. This implies that consumer attention to billing is highest during billing months that are followed closely by cold-weather months that require heating, when households can react to cost signals. On the other hand, responsiveness to heating expenses are low during off-heating months, because salience is diminished considerably.

Coefficients on energy demand for the other treatment billing cycles (February, March, October, November, and December) are not statistically significant. Given the dearth of observations for accounts billed during non-summer months, this result may be due to lack of statistical power in estimation. Nonetheless, the pattern consistently indicate that insalience of energy costs is less of a concern during months that require heating. See Figure 3.3: Plot A for a visual representation of the regression results in columns 1 and 2.

Overall, the results suggest that households are most inattentive to annual heating bills that are received during the summer. They tend to react to costs in the few months post-billing and unable to respond to the heating costs billed during the summer because heating choices take place during the winter – by then, the heating bill has become less relevant to household expenses. I further address the strength of this mechanism in the next subsection.

3.5.5 Water Heating

For the majority of the buildings, heating bills cover costs incurred for water heating, in addition to space heating. Although energy consumed for hot water is a smaller share of total annual energy costs, households could react to costs on bills by adjusting the use of hot water instead. Residential demand for energy to heat water is less seasonal than that for space heating, however. Households that are indeed paying attention to bills during the summer months may react by adjusting (disproportionately) the amount of energy they consume for water heating, in the shower and in the kitchen, for example. This would potentially bias the main results had I considered total energy consumption. To test for consumer inattention, I considered energy consumed for space heating independently.

Now I check the extent of consumption adjustments via water heating. I limit the sample of buildings to only those that are billed for both space and water heating, and estimate the preferred equation on energy demand for both space and water heating (in kilowatt hours per square meter of living space). In the third column of Table 3.12, I confirm the main quantitative findings for space heating.

In the fourth column of Table 3.12, I directly investigate whether the timing of bills affects energy consumed for heating water. Indeed, I find evidence that households billed during the off-heating months reduce energy demand for heating water. More importantly, this serves as a placebo test for the presumed salience mechanism in determining annual heat energy demand. I interpret this as providing strong evidence that the temporal distance between bills and the winter season is the main driver behind the salience bias in energy consumption for space heating – leading consumers to demand more energy on net. See Figure 3.3: Plot B for a visual representation of the regression results in columns 3 and 4.

In the last column of Table 3.12, I estimate the preferred equation for buildings billed only for space heating. As expected, I find that salience bias in heat energy consumption is more prevalent. Without the option to adjust water heating, results suggest that households consume significantly more heat energy than the control group when billed in the spring months of March and April as well.

3.6 Distributional Effects

Often we are interested not only in the average treatment effect (ATE) for a population, but also the conditional average treatment effects (CATE). More specifically, we may also be interested in the spatial disaggregation of the average effect to understand the socioeconomic distribution of the costs and benefits of policy recommendations.

In this section, I take advantage of this empirical setting to investigate whether salience effects of heating bills varies with the regional heterogeneity in Germany. It is possible to do so because the natural experiment of billing cycles applied nationwide. Here I consider specifically whether the magnitude of the average treatment effect varies meaningfully with the rate of unemployment, measured at the zip code level.

3.6.1 Unemployment Disparities

Is the treatment effect higher for communities that experience higher unemployment rates?[14] To estimate the heterogeneity in the ATE with respect to the unemployment rate, I first create terciles of the unemployment rate distribution and then proceed to estimate the preferred specification for oil buildings separately for the terciles.

Table 3.13 presents descriptive statistics of key variables discussed in this paper by terciles of the unemployment rate in 2009 for houses using oil for heating fuel. As expected the communities in the top tercile have on average lower purchasing power per household, more likely to be living in the East of Germany, and in larger multi-apartment buildings.

[14]Here I make the implicit assumption that buildings located in zip codes with high (low) unemployment rates are home to households that experience high (low) unemployment.

3.6.2 Subgroup Treatment Effects

Under the reasonable assumption that poorer households with cash constraints tend to be more attentive year-round to costs and billing information, I would expect that the receipt of bills during low-usage months (when salience of energy consumption costs is diminished) would not induce poorer households to over-consume as much as households that are economically more secure (lower unemployment rates).

Table 3.14 may suggest the opposite of my hypothesis. The first column estimates the conditional average treatment effects for buildings that are located in zipcodes in the first tercile with mean unemployment rate of 2.7%. The second column estimates the CATE for the second tercile with mean unemployment rate of 5.0%. The third column presents the findings for the top third of the unemployment rate distribution with mean unemployment rate of 9.9%. Finally, the last column produces the average treatment effect for the full distribution of the unemployment rate for comparison purposes. In general, there is suggestive evidence for treatment effect heterogeneity – salience bias during the summer months is higher in poorer socioeconomic neighborhoods. However, this effect heterogeneity seems to be driven by fixed differences between the terciles[15].

At any rate, heating costs are a higher share of disposable income for households with tighter budgets and thus there exists distributional concerns as a consequence of billing cycles that end during the summer. If it is indeed the case that they are more affected by consumer inattention to heating bills, then the adverse welfare implication of salience bias is compounded.

3.7 Robustness

In the next paragraphs, I test the robustness of the main results for building using heating oil. In particular, I want to rule out the possibility that the results are driven by an unobserved confounding factor. That is, it should not be the case that buildings that are on the calendar year billing cycle are somehow different from the other buildings in some unobserved dimension that may be correlated with energy consumption. For example, there may be concerns that calendar year billing cycles apply to more energy-efficient buildings and/or are chosen by more energy-saving households.

[15] Poorer households tend to live in more energy-inefficient buildings and have cash-constraints, for instance. Based on data from energy performance certificates for the sub-sample of buildings using heating oil, buildings observed in zip codes with higher unemployment rates were on average older and less likely to meet the 1995 thermal insulation standards.

3.7.1 Heating vs. Non-Heating Months

To check this, I exclude buildings billed for the calendar year from the sample of buildings using oil. Then I pool non-heating (summer) and heating months to redefine treatment and control groups more flexibly. Now the control group contains all buildings with billing periods that start in September, October, November, December, February, and March. Note that now I cluster the standards errors at the zip code level to further allay concerns.

Table 3.15 presents evidence on the robustness of the main results. The first two column report the average treatment effect for buildings billed during the summer months of May to July. In the last two columns, I add April and August to the treatment group. The average treatment effect is about 4 percent over-consumption due to poor salience of heating bills during the summer. These results support the validity of the main estimation results.

3.7.2 Energy Performance Scores

There might still remain the concern that for some reason, buildings that are newer and thus more energy-efficient (due to building codes or simply better technology, for instance) are billed during the winter heating season. I limit the sample of buildings using heating oil to a subset, for which I have information on energy performance certificates. These certificates were issued to the buildings from 2008 to 2018, largely issued in 2008, and I matched them to the primary data on consumption bills (about 40% of the observations). I further split the sample into classes of building codes[16] and report the average year of construction by billing cycles. Table 3.16 shows that the mean age of buildings are almost identical across billing cycles except for buildings built before the building codes were introduced. For building built before 1919, buildings with calendar year billing are newer than average. However, this is not the case for buildings built from 1919 to 1977.

Note that the sample of buildings reporting energy performance scores is possibly more energy-efficient than the full sample, because the building owner's decision to produce the EPC is likely correlated with recent energetic-renovations in the past that affect energy consumption of these buildings. And therefore, the building year is not a precise or complete measure to learn about the energy performance of these buildings.

Moreover, the energy performance score is likely an endogenous explanatory variable in this setting, because majority of energy performance scores ("Verbrauchsausweis") are

[16]Energy efficiency regulation in Germany has largely taken the form of building codes, defining the building-aggregate maximum annual energy requirement per square meter of living space for newly constructed homes. The Heat Insulation Ordinance was first introduced in 1977, amended and made progressively more stringent in 1984 and 1995. It was replaced by the Energy Saving Ordinance in 2002. Note that there were no minimum energy standards for buildings built before 1978.

measured using building-level consumption that took place in the past years (which would include the any effect of consumer inattention to costs and bills due to intermittent and untimely billing – the main thesis of this paper.)

Notwithstanding these important caveats, I redo the main estimation for buildings using heating oil using fixed effects for building codes, and year of construction and reported energy performance score as further controls to check whether average treatment effects are sensitive to the inclusion.

Table 3.17 shows that differences in these energy-performance metrics measured across billing cycles do make a difference in the magnitude of the results, but the conclusions of the main results are robust to these conservative specifications. Column 1 shows the preferred model on the subsample of buildings with energy performance certificates. Column 2 adds fixed effects for building code regulation which controls for differences in the efficiency standards based on the date of construction. The model in Column 3 further includes the year of construction as a covariate. Column 4 uses the minimum reported performance score irrespective of the year when the EPC was issued, while in column 5 the sample is limited to only those buildings with performance certificates issued in the year 2008.

3.7.3 Buildings Built Before 1978

In order to further limit any bias arising from differences in energy-efficiency of buildings on different billing cycles, I focus only on the subset of observed buildings that were built before 1978, and therefore did not fall under any thermal insulation standards during construction.

Table 3.18 reports the ATE by type of buildings (two-family houses, 3 to 6 multi-family buildings, 7 to 12 multi-apartment buildings, and buildings with 13 apartments units or more). Results indicate the energy consumption by two-family homes is even more sensitive to the timing of bills – with salience bias up to 15 percent for bills starting in the summer month of June. This may be a particularly noteworthy result because close to half the building stock (owned and rented) by German families are one-to-two family unit buildings (Destatis, 2016).

3.7.4 Munich and Stuttgart

Here I limit the analysis to buildings using heating oil in the large urban cities of Munich and Stuttgart for two main reasons:

- the share of buildings with calendar year billing cycles is less than 50 % (41%

in Stuttgart and 46 % in Munich). The corresponding share in the other major German cities of Berlin, Hamburg, Cologne, Frankfurt (Frankfurt am Main) are much larger (60 to 70 %).

- the housing supply shortages are particularly acute in Stuttgart and Munich, and the associated market tightness means that any bias arising due to household selection into different billing cycles is plausibly absent.

To identify the urban regions of Stuttgart and Munich, I limit the sample to buildings located in their respective regional planning regions ("Raumordnungsregionen" or ROR). Number 810 represents Stuttgart (3,850 buildings) and number 910 (3,417 buildings) represents Munich).

Table 3.19 presents the results for buildings located in these regions. Estimates indicate a large salience effect of 6 percent for buildings billed during the summer. Stuttgart and Munich fall in the lowest tercile of unemployment rates and over-consumption of heat energy exists, when billing occurs during months that are marked by the lowest share of total annual heating degree days in the 3 months post-billing.

3.8 Long-term Investments

Thus far, I have remained silent on how building-level investments in energy-efficiency technology (thermal insulation or heating fuel efficiency in this context) may have been affected over the long-run by enduring differences in the salience of heating bills and thus energy cost expenditures. I address this topic directly in this section and identify the relative importance of inattention to energy-efficiency decisions for residential apartment buildings - one of the first estimates in the literature (Gerarden et al., 2017).

Keeping all else equal, I expect that homes that incur annual higher expenditures for energy consumption to have higher incentives to invest in thermal efficiency to save on energy costs. In the previous sections, I show that apartment buildings that are billed during the summer season are prone to above-optimal consumption levels, which translates into higher annual costs of home heating. Given this backdrop, I empirically test whether persistent positive exogenous shocks to energy costs and thus financial incentives, led to statistically significant differences in investments by building owners in energy-efficiency technology.

I perform this test using data from energy performance certificates that were issued between 2014 and 2019 to buildings using heating oil and constructed before 1978, i.e. they were not subject to building standards. This allows me to plausibly argue that any detectable differences in thermal insulation standards are due to investments in renovations post-construction and not due to federal building codes.

Table 3.20 provides summary statistics of the sample. Using energy performance certificates issued starting 2014, I observe data on (1) the year of construction or year of latest renovation of key building component that are associated with heat energy efficiency, and (2) whether the building component meets efficiency standards regulated under WSVO 1995 (building-level thermal insulation standards).

Panel A shows that the mean age of building is statistically identical (p-value 0.1774) across treatment and control groups. This is also true for the basement ceiling, but fails for all other thermal-insulation features of the roof, loft, outer wall surface, and windows.

Panel B shows even more interesting descriptive statistics. The first column under "Overall" indicates how may of the five building components (roof, loft ceiling, outer wall, windows, and basement ceiling) were certified to meet thermal insulation standards under WSVO 1995. On average, buildings with summer billing accounts were associated with a higher share of key building components that met the 1995 thermal-insulation standards.

Now I test my hypotheses of differences in energy-efficiency investments in a more systematic manner – using a regression model that controls for observable characteristics of buildings and zip code/location. I use the following baseline linear probability model with fixed effects to estimate differences in heating-efficiency investments across billing cycles:

$$y_i = \alpha + \beta \text{May to July}_i + \delta \text{Year Built}_i + \gamma_{\text{Size}} + \theta_{\text{PLZ}} + \lambda_t + \epsilon_i \tag{3.5}$$

where y_i in an indicator for whether each of the seven measures (overall, heater, roof, outer wall, loft, windows, and basement) of building i meets the thermal insulation standards set out in WSVO 1995 regulation, at the time of certification. For the heating system, I use the indicator for whether the year of heating system installed is greater or equal to 1995.

- May to July$_i$ indicates whether the billing cycle (the starting month) associated with the building i started in May, June, or July. The control group is buildings with calendar year accounts.
- Year Built$_{it}$ captures the year in which the building was newly constructed.
- γ_{Size} and θ_{PLZ} capture the building size and zip code fixed effects respectively.

- λ_t are fixed effects for the year in which the EPC was issued and ϵ_i the error term, clustered at the zip code level.

Table 3.21 demonstrates that building owners treated with summer billing cycles invested to retrofit a higher share of the building envelope to meet the 1995 thermal insulation standards, captured by the variable "overall". The estimate of 0.231 translates to a 4.3 percent increase in the share of building components receiving an insulation upgrade that met the 1995 standards. This estimate was likely powered by higher investments in insulating the roof, exterior wall, and windows. The windows components was particularly affected – with an increase of 9 percent share of buildings that received renovation meeting the 1995 insulation standard. I do not find any statistically significant differences in the shares for the loft and basement ceiling, however.

Although the economic significance of these differences in investment rates across billing cycles may not be high, the results in this section do provide some evidence that long-term financial incentives for energy-efficiency do matter, and owners of multi-apartment buildings responded to differences in expected returns to investments in energy-efficiency – at least for buildings built before 1978, associated with low rates of renovation (Ray and Sunikka-Blank, 2013).

These results show that salience of costs affect not only short-term consumption behaviour of tenants/residents, but also feed into long-run investment decisions of building owners. Any energy-efficiency gaps, due to lack of investments into heat energy efficiency, for instance, can be optimally bridged by drawing the user's attention to true energy costs – by improving the salience of billing information.

With respect to salience bias in energy consumption, the results in this section further imply that the short-run estimates are likely even higher, all else equal. The results captured in this paper capture the effect of attention bias over the long-run, after learning and investment adjustments have taken place as result of the treatment. I confirm this in Section 3.9.3 by considering a sample of buildings that are as similar as possible in meeting thermal-insulation standards.

3.9 Other Energy Sources

In this section, I show that the results are not limited to buildings using heating oil.

3.9.1 Natural Gas

I consider buildings that use natural gas as the main heating fuel. Interestingly, I find that newer buildings using natural gas were more likely to be on the calendar year billing cycle. In Table 3.22, I estimate the preferred model on the full sample and find that all billing accounts were associated with higher heat energy demand relative to the control group of calendar year billing. This pattern re-emerges once I limit the sample to those buildings with energy performance certificates in column 2.

I account for this bias in treatment assignment using fixed effects for building codes that were applicable by year of construction[17]. In Columns 3 and 4, I show that buildings billed during the off-heating season are subject to consumer inattention to costs during the winter. The results are robust to controlling for the minimum energy performance scores. There may still exist a positive likelihood for selection bias if older buildings that were renovated and switched to natural gas fuel were more likely to be assigned the calendar year billing cycle. For this reason, I consider a sample of buildings that are comparable on all observable energy efficiency measures in Section 3.9.3.

3.9.2 District Heating

I further consider buildings that used district heating and to improve precision of my estimates I pool the non-heating months of May, June, and July. Note that the control group includes only calendar year billing. Similar to buildings heated with natural gas, I find some bias in billing cycle assignment by age of the building (see Table 3.23). After adding in the fixed effects for building codes, however, the estimate for salience bias in energy consumption is robust to further controls.

3.9.3 Buildings with WSVO 1995 Standard

Finally, I construct a subsample of buildings that meet the building standards mandated under the thermal insulation regulation of 1995 (WSVO 1995). Because the average age of buildings in the full sample is 1967 and over 80 % of the buildings were built before 1995 ("Altbau"), achieving the 1995 standard is arguably a suitable benchmark for good energy performance of buildings[18].

I classify a building to meet WSVO 1995, if it was certified that all five building com-

[17]Alternatively: I limit the sample of buildings to those built before 1978 and recover a pattern of overconsumption, consistent with non-salience of energy costs during the non-heating months. The estimates (available by request) are of higher magnitudes compared to estimated treatment effects for all buildings. More importantly, Table 3.22 show that salience bias in heat consumption exists, irrespective of building age.

[18]I am unable to consider stricter thermal insulation standards due to lack of data.

ponents (the roof, loft ceiling, outer wall, windows, and basement ceiling) meet the 1995 minimum energy-saving standards. Using this subsample, I seek to examine buildings that are as comparable as possible in terms of energy-efficiency investments and insulation performance. I pool non-heating billing months of May to July to form the treatment group, while calendar year billing remains the control group. The result that follow are robust to clustering at the zip code level.

Table 3.24 presents the findings. In column 1, I estimate the preferred equation for buildings using natural gas that meet the 1995 thermal insulation standards. In the next column, I further account for any remaining differences in energy performance of buildings by controlling for the year of construction, year of the heating system, along with fixed effects for building energy-standards. The rate of over-consumption due to non-salience stays close to 9 percent. In the last column, I expand the sample by including buildings using heating oil and district heating, while adding fixed effects for fuel type, and find approximately the same quantitative result.

I interpret these results as strong evidence that over-consumption due to poor salience of heating bills is pervasive and not limited to buildings that use heating oil or to buildings with poor energy-efficiency standards. I conclude that there exists economically significant potential to conserve energy via behavioural changes using appropriately-timed bills to improve salience of energy costs.

3.10 Qualifications and Extensions

Following are some caveats to the empirical results:

I do not observe directly the level of attention households pay to bills and how this differs by month of bill receipt. Moreover, I do not know the exact date building managers distribute the bills to the residents - this is less of an issue, however, for small apartment buildings and homes that use heating oil.

The belief about the exogeneity of billing periods or cycles is central to removing unobserved selection bias in estimating treatment effects. The setup does not allow to fully control for household-specific factors. However, given that I measure building-level consumption, I do not expect households living in buildings with summer accounts versus winter accounts to be systematically different on the aggregate (in income and preferences for heating, for example), conditioning for building characteristics and location.

One important area of future research would be to quantify the extent to which split incentives between landlords and tenants led to differences in long-term efficiency investments. Do landlords with tenants underinvest compared to home-owners, all else equal? To answer this question, one can replicate the analysis in this paper for a data sample of single-family homes, distinguishing between owner-occupied and rented-homes.

3.11 Conclusion

By exploiting the billing cycle assignment in a large scale natural experiment in Germany, I estimate a causal over-consumption of heating energy by buildings that are billed during the summer months, and thus are treated with low salience of energy costs. Empirical results in this paper are theory consistent. Effective attention to costs take place in the few months immediately after billing. Consequently, consumers billed for heating during off-winter months are subject to consumer inattention, leading to their perceived cost of consumption to be lower – resulting in above optimal heat energy demand. Results demonstrate that buildings that are billed for space heating during the summer consume on average up to 9 percent more than those that are billed for the more common calendar year billing cycle.

This research highlights the importance of improving the salience of information on energy prices and consumption to encourage consumer attention and alter household behaviour. Engaging energy users with bills during high-consumption events has significant potential to achieve energy savings in the building sector, both in the short- and long-run, without additional investments for technical building efficiency.

This paper further examines whether differences in consumer inattention to energy costs had a long-term impact on technology choices and investments. I find evidence that building owners reacted to higher annual heating expenditures by investing in long-term thermal insulation of buildings. This result is evidence that under-investment (the energy-efficiency gap) in heat energy-efficiency due to the split-incentive problem between landlords and tenants may not be as high as previously thought. These decisions to retrofit were driven by distortions in financial incentives, due to salience bias in household consumption, rather than energy-efficiency shortcomings of buildings billed during the summer. Notwithstanding, these results illustrate that investments in energy upgrades for existing buildings did respond to energy cost shocks.

In Germany, the heating sector is primarily powered by fossil-fuels and accounts for 25% of the final energy consumed, of which about 70% is consumed by the residential sector (AGEB, 2018). The results in this paper indicate that the current billing system that is used for the vast majority of buildings in Germany is not optimal for reaching energy and environmental policy targets. Ultimately, those households that want to save on bills or conserve heating energy must know the heating costs, with timely information or costs of attention to be as low as possible. This is likely to be increasingly important given the recent discussion of a CO_2 price on the heating sector (mainly for buildings) in Germany. Providing homes with heating bills during the peak of winter (relevant information at the relevant time) is arguably not more costly than status-quo, but it does have the high potential to reduce energy consumption from the household sector.

Table 3.1: Heating Needs During the Year

		Heating Degree Days (HDD)		
Month	Mean Temperature	Monthly	12-month sum	3-month sum
January	0.52	449.0	2426.2	1184.1
February	0.68	404.2	2424.5	911.4
March	4.33	330.9	2414.3	590.1
April	9.26	176.3	2412.0	284.9
May	13.23	82.9	2409.8	118.5
June	16.59	25.7	2414.3	48.2
July	18.60	9.9	2414.3	79.1
August	17.82	12.6	2414.5	245.2
September	14.09	56.6	2414.4	529.0
October	9.40	176.0	2413.6	878.1
November	5.12	296.4	2404.6	1149.3
December	1.92	405.6	2405.8	1247.0
Total	9.30	202.2	2414.0	605.4

Notes: The second column reports heating degree days during each month, calculated as the total sum of differences between the daily mean temperature and the heating limit of 15 degree Celsius on days with recorded mean temperatures less than 15 degrees. The values are calculated by the author using daily observations from 20030101 to 20181231 at 204 nearest weather stations to 8303 zipcodes in Germany. In the mapping used, average distance between zip code and nearest weather station is 18.3 km, with standard deviation of 10.4 km, minimum and maximum distance of 0.076 km and 59.86 km respectively. Source: Deutscher Wetterdienst (DWD).

Table 3.2: Incidence of Billing Accounts by Fuel Type

Fuel Type	March - July	August - February	December	Share
Natural Gas H	0.16	0.84	0.68	0.59
Oil	0.39	0.61	0.49	0.32
District Heating	0.15	0.85	0.76	0.08
Natural Gas L	0.00	1.00	0.21	0
Other	0.24	0.76	0.64	0.01
Total	23 %	77 %	62 %	

Notes: The first two columns show the share of buildings in year 2008 with annual heating bills ending in March to July and August to February. The December column indicates the share of buildings with accounts ending in December (calendar year billing). The last column reports the share of buildings by heating fuel type observed in 2008, sample of over 250,000 buildings. "Other" fuel types consist of LPG, pellets, electricity, wood, coal, brown coal, steam, coke, and others.

Table 3.3: Billing Cycles by Building Size – Heating Oil Homes

	Number of Apartments/HH								
End of Billing	2	3	4	5	6	7	8	9	10
January	2.2	1.6	1.5	1.1	0.8	0.9	0.4	0.6	0.6
February	2.3	1.6	1.6	1.4	0.6	0.9	0.8	0.6	0.4
March	3.6	3.1	2.3	2.0	1.8	1.7	1.5	1.2	0.7
April	5.3	5.0	4.3	4.1	3.7	4.3	4.0	5.3	5.3
May	23.2	27.5	26.4	22.9	22.2	19.7	17.9	18.3	14.5
June	8.2	8.1	7.2	7.0	6.2	6.3	6.6	6.7	6.6
July	3.3	2.5	2.1	1.8	1.5	1.2	1.2	0.8	1.0
August	3.2	2.6	2.1	2.1	1.0	1.2	1.2	0.9	1.2
September	5.2	4.3	3.6	3.8	2.6	2.8	1.6	2.4	1.5
October	2.6	2.0	1.7	1.3	0.9	1.1	1.2	1.1	0.6
November	1.6	1.4	1.3	1.0	0.8	0.7	0.8	0.9	0.5
December	39.3	40.4	45.9	51.5	57.6	59.2	62.7	61.2	66.9
April to June	36.6	40.6	38.0	34.0	32.1	30.3	28.6	30.3	26.5

Notes: The table shows the distribution of billing cycles observed in 2008 for all buildings with up to 10 apartments that use heating oil as fuel.

Table 3.4: Billing Cycles by Building Size – Natural Gas Homes

	Number of Apartments/HH								
End of Billing	2	3	4	5	6	7	8	9	10
January	2.6	2.7	2.2	2.0	1.3	1.8	1.5	1.6	0.9
February	2.9	2.4	2.1	2.1	1.7	1.8	1.5	1.5	1.8
March	4.0	3.7	3.4	2.8	2.5	2.7	2.4	1.9	2.1
April	4.4	3.9	3.6	3.0	2.8	2.6	2.3	2.2	2.5
May	7.0	7.3	6.0	5.5	4.3	5.0	4.2	3.5	3.6
June	5.1	5.3	4.7	4.1	3.7	4.1	3.6	3.8	3.3
July	1.8	1.5	1.3	1.2	0.9	1.0	1.0	1.1	0.9
August	2.6	2.2	1.9	1.7	1.5	1.7	1.4	1.1	1.2
September	8.2	7.0	6.6	5.4	5.3	4.8	4.5	3.7	3.9
October	5.3	4.5	3.9	3.2	2.7	2.7	2.0	2.1	2.1
November	3.7	3.5	3.1	2.6	2.4	2.6	2.0	2.0	1.3
December	52.4	56.2	61.3	66.4	70.9	69.2	73.6	75.4	76.5
April to June	16.5	16.4	14.3	12.6	10.8	11.7	10.0	9.5	9.3

Notes: The table shows the distribution of billing cycles observed in 2008 for all buildings with up to 10 apartments that use natural gas as fuel.

Table 3.5: Billing Cycles by Building Size – District Heating Homes

	Number of Apartments/HH								
End of Billing	2	3	4	5	6	7	8	9	10
January	1.7	3.	2.1	1.3	1.2	1.1	0.9	1.2	1.6
February	1.4	1.7	1.7	1.8	1.0	0.6	1.0	1.3	1.7
March	3.1	3.3	3.1	1.9	2.0	2.3	1.9	2.3	1.6
April	2.4	3.3	4.6	2.2	1.8	1.8	2.8	1.7	2.7
May	4.1	4.6	3.0	5.6	5.3	3.2	4.4	5.1	3.6
June	8.0	6.5	8.7	8.0	6.8	9.8	10.4	11.7	12.0
July	1.7	1.5	1.0	1.4	1.2	1.4	0.9	1.2	1.7
August	2.2	2.9	1.6	2.0	1.8	1.2	1.2	1.2	1.6
September	3.1	3.5	2.9	2.8	3.8	2.5	3.7	3.6	4.9
October	2.0	2.4	1.5	2.1	2.5	1.3	1.2	1.7	1.0
November	2.6	1.5	0.8	1.0	0.9	1.1	1.0	0.7	0.7
December	67.8	64.8	68.9	69.9	71.8	73.7	70.6	68.2	66.8
April to June	14.5	14.4	16.3	15.8	13.9	14.9	17.6	18.5	18.3

Notes: The table shows the distribution of billing cycles observed in 2008 for all buildings with up to 10 apartments that have district heating.

Table 3.6: Balance Test - Differences in Mean Price

Euros per kWh by Month of Billing Start

	Heating Oil		Natural Gas H		District Heating	
Bill Start	All	Apts<11	All	Apts<11	All	Apts<11
Constant	0.0643	0.0643	0.0670	0.0674	0.0961	0.0952
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
February	-0.0007	-0.0007	0.0014	0.0016	-0.0047	-0.0037
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
March	-0.0003	-0.0003	0.0008	0.0010	-0.0055	-0.0056
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
April	0.0000	-0.0000	0.0006	0.0008	-0.0078	-0.0071
	(0.89)	(0.96)	(0.00)	(0.00)	(0.00)	(0.00)
May	0.0010	0.0008	0.0004	0.0004	-0.0035	-0.0000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.97)
June	0.0006	0.0006	0.0011	0.0013	-0.0049	-0.0051
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
July	0.0002	0.0002	0.0000	-0.0003	-0.0091	-0.0068
	(0.00)	(0.00)	(0.97)	(0.00)	(0.00)	(0.00)
August	-0.0005	-0.0005	0.0002	0.0002	-0.0051	0.0026
	(0.00)	(0.00)	(0.44)	(0.30)	(0.00)	(0.00)
September	0.0001	0.0001	0.0004	0.0005	-0.0059	-0.0065
	(0.34)	(0.54)	(0.00)	(0.00)	(0.00)	(0.00)
October	-0.0001	-0.0002	-0.0005	-0.0006	0.0030	0.0004
	(0.04)	(0.01)	(0.00)	(0.00)	(0.00)	(0.65)
November	-0.0004	-0.0004	-0.0003	-0.0001	-0.0089	-0.0075
	(0.00)	(0.00)	(0.00)	(0.17)	(0.00)	(0.00)
December	-0.0004	-0.0004	-0.0001	0.0001	0.0042	0.0021
	(0.01)	(0.00)	(0.53)	(0.47)	(0.00)	(0.08)
Observations	809,754	725,829	1,630,852	1,270,465	287,809	102,721
Adj R^2	0.416	0.414	0.028	0.032	0.026	0.023

Notes: Table reports coefficients from simple regressions of heating costs incurred per unit of energy (kWh) on the starting month of the billing period, with fixed effects for the year and building size, and robust standard errors. The omitted month is January which corresponds to the calendar year billing cycle, the control group. I discard observations with yearly consumption below 1 kWh/m^2 and price per kWh above 1 Euro (0.1% of total). Constant reports the average price per kWh that was paid by buildings in the control group. p-values are reported in parentheses.

Table 3.7: Descriptive Statistics - Oil Units

Bill Start	kWh/m^2	Price	# of Apts	Apt Size	PP per HH	# of Bills
January	126.31	6.47	7.21	90.04	45.15	488,921
February	120.43	6.46	3.51	89.32	46.36	11,422
March	119.68	6.49	3.49	91.23	46.61	12,344
April	122.08	6.54	3.99	89.51	46.49	22,495
May	130.22	6.64	6.20	85.10	44.97	41,157
June	127.15	6.62	4.40	83.95	45.60	167,029
July	126.76	6.63	5.47	88.44	45.77	57,592
August	124.79	6.53	3.81	89.84	46.79	17,104
September	121.79	6.59	3.79	91.00	46.22	17,892
October	122.52	6.57	4.12	91.11	46.07	30,972
November	121.55	6.54	3.95	88.89	46.26	15,349
December	121.93	6.57	4.13	89.56	45.86	10,778
All Bills	126.02	6.53	6.01	88.59	45.46	893,055

Notes: The table reports average values calculated using bills from 200801 to 201806 for buildings using heating oil as the main fuel. The first column reports the annual heat energy consumption per square meter of living space. I discard bills that report yearly consumption below 1 kWh/m^2. Price of heating fuel is given in euro cents per kWh. Building size is given by the column indicating the number of apartments. Apartment size reports the average size of the apartment in a building in heated living space in square meters. PP per HH is the purchasing power per households at the zip code level (Source: RWI and microm 2020).

Table 3.8: Response of Heat Energy Consumption to Summer Billing I

Oil Units & All Building Types

Bill Start	*Dependent variable*: ln (kWh/m^2)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
May	0.0455***	0.0463***	0.0404***	0.0402***	0.0249***	0.0214***	0.0215***	0.0218***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
June	0.0476***	0.0475***	0.0389***	0.0388***	0.0441***	0.0400***	0.0386***	0.0356***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
July	0.0239***	0.0239***	0.0140**	0.0139**	0.0249***	0.0210***	0.0205***	0.0196***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Costs per kWh		-0.0261*	-0.0259*	-0.0259*	-0.0259*	-0.0227*	-0.0225*	-0.0225*
		(0.011)	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)
HDD 12 month sum				Y	Y	Y		Y
Purchasing Power per HH						Y		
Year FE			Yes	Yes	Yes	Yes	Yes	Yes
# of Apts FE	Yes	Yes	Yes	Yes				
# of Apts X State FE					Yes	Yes		
# of Apts X PLZ FE							Yes	Yes
N	754,868	672,735	672,735	672,735	672,686	569,047	670,234	670,234
Adj R^2	0.010	0.017	0.042	0.042	0.082	0.083	0.316	0.323

Notes: The omitted month is January (the most common starting month for billing), the control billing cycle. Standard errors clustered at the building level and robust to heteroskedasticity. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.9: Response of Heat Energy Consumption to Summer Billing II

Oil Units & Buildings with up to 10 Apartments

Bill Start	*Dependent variable*: ln (kWh/m^2)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
May	0.0393***	0.0382***	0.0323***	0.0319***	0.0284***	0.0254***	0.0210***	0.0215***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
June	0.0504***	0.0502***	0.0418***	0.0416***	0.0474***	0.0433***	0.0388***	0.0360***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
July	0.0261***	0.0264***	0.0168***	0.0166***	0.0270***	0.0226***	0.0204***	0.0196***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Costs per kWh		-0.0184**	-0.0182**	-0.0182**	-0.0185**	-0.0178**	-0.0185**	-0.0186**
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
HDD 12 month sum				Y	Y	Y		Y
Purchasing Power per HH						Y		
Year FE			Yes	Yes	Yes	Yes	Yes	Yes
# of Apts FE	Yes	Yes	Yes	Yes				
# of Apts X State FE					Yes	Yes		
# of Apts X PLZ FE							Yes	Yes
N	666,376	593,135	593,135	593,135	593,135	503,095	591,765	591,765
Adj R^2	0.009	0.013	0.040	0.040	0.070	0.071	0.277	0.284

Notes: The omitted month is January (the most common starting month for billing), the control billing cycle. Standard errors clustered at the building level and robust to heteroskedasticity. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.10: Interaction with Heating Degree Days

Oil Buildings

Bill Start	Dependent variable: ln (kWh/m^2)					
	(1)	(2)	(3)	(4)	(5)	(6)
May to July	0.031***	0.031***	0.042***	0.018	0.038*	0.040**
	(0.0062)	(0.0090)	(0.0116)	(0.0146)	(0.0149)	(0.0127)
X (HDD/100) 1-month sum	-0.018***					
	(0.0051)					
X (HDD/100) 2-month sum		-0.015***				
		(0.0038)				
X (HDD/100) 3-month sum			-0.014***			
			(0.0029)			
X (HDD/100) 4-month sum				-0.003		
				(0.0015)		
X (HDD/100) 5-month sum					-0.001	
					(0.0010)	
X (HDD/100) 6-month sum						-0.001
						(0.0009)
N	670,234	670,234	670,234	670,234	670,234	670,234
Adj R^2	0.323	0.323	0.323	0.323	0.323	0.323

Notes: The control billing cycle is the calendar year. Each column reports coefficients on the interaction between the pooled treatment group and the annual sum of heating degree days recorded 1 month to 6 months post-billing. In addition to the X-month HDD covariate corresponding to the interaction term, all regressions controlled for heating costs per kWh, 12-month HDD, building size by zip code fixed effects, and year fixed effects. Robust standard errors clustered at the building level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.11: Dynamics of Salience

Oil Buildings

Bill Start	ln (kWh/m^2)
	(1)
May to July	-0.006
	(0.0149)
X (HDD/100) 1st month	-0.042***
	(0.0054)
X (HDD/100) 2nd month	-0.033***
	(0.0072)
X (HDD/100) 3rd month	-0.029***
	(0.0051)
X (HDD/100) 4th to 6th month	0.009***
	(0.0020)
X (HDD/100) 7th to 12th month	0.007***
	(0.0010)
N	670,234
Adj R^2	0.324

Notes: The control billing cycle is the calendar year. Table reports coefficients on the interaction terms between the pooled treatment group and the heating degree days recorded in the 1st, 2nd, 3rd, 4th to 6th, and 7th to last month of the billing cycle. In addition to all HDD variables corresponding to the interaction terms, the control set included heating costs per kWh, building size by zip code fixed effects, and year fixed effects. Robust standard errors clustered at the building level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.12: Response of Heat Energy Consumption to Billing Cycles

Oil Units - Cost Salience

Bill Start	*Dependent variable*: ln (kWh/m^2)				
	(1)	(2)	(3)	(4)	(5)
	Space	Space	Space	Water	Space Only
February	-0.014	-0.007	-0.005	-0.004	0.013
	(0.0101)	(0.0103)	(0.0115)	(0.0169)	(0.0232)
March	-0.011	0.004	0.006	-0.013	0.053*
	(0.0093)	(0.0105)	(0.0117)	(0.0186)	(0.0236)
April	-0.003	0.020*	0.017	-0.038*	0.056**
	(0.0074)	(0.0102)	(0.0116)	(0.0176)	(0.0202)
May	0.022***	0.049***	0.050***	-0.035	0.042*
	(0.0054)	(0.0099)	(0.0115)	(0.0184)	(0.0175)
June	0.037***	0.066***	0.073***	-0.029	0.044**
	(0.0030)	(0.0092)	(0.0107)	(0.0168)	(0.0158)
July	0.021***	0.049***	0.058***	-0.064***	0.027
	(0.0046)	(0.0096)	(0.0112)	(0.0179)	(0.0170)
August	0.009	0.033**	0.031*	-0.040*	0.064**
	(0.0081)	(0.0108)	(0.0123)	(0.0187)	(0.0245)
September	0.001	0.018	0.028**	-0.050**	-0.017
	(0.0076)	(0.0091)	(0.0104)	(0.0164)	(0.0205)
October	0.003	0.010	0.005	-0.048***	0.002
	(0.0062)	(0.0066)	(0.0074)	(0.0116)	(0.0161)
November	-0.012	-0.012	-0.001	0.004	-0.038
	(0.0085)	(0.0085)	(0.0096)	(0.0156)	(0.0206)
December	-0.009	-0.012	-0.021	-0.013	0.006
	(0.0099)	(0.0099)	(0.0112)	(0.0181)	(0.0266)
Costs per kWh - Space	-0.022**	-0.022**	-0.064**		-0.020**
	(0.0086)	(0.0086)	(0.0219)		(0.0075)
Costs per kWh - Water				-0.017**	
				(0.0062)	
HDD 12 month sum	Y	Y	Y	Y	Y
HDD 3 month sum		Y	Y	Y	Y
Year FE	Yes	Yes	Yes	Yes	Yes
# of Apts x PLZ FE	Yes	Yes	Yes	Yes	Yes
N	794,666	794,666	584,069	586,631	209,543
Adj R^2	0.302	0.302	0.299	0.290	0.447

Notes: The omitted month is January (the most common starting month for billing), the control month group. Standard errors clustered at the building level and robust to heteroskedasticity. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.13: Descriptives by Terciles of the Unemployment Rate

Oil Units in 2009

Quantile	T1	T2	T3	Full Sample
Unemployment %	2.72	5.03	9.94	5.55
Purchasing Power per HH	45.80	42.12	35.98	41.74
Annual kWh/m^2	128.35	136.82	144.85	136.10
Costs per kWh	0.061	0.061	0.061	0.061
No. of Apartments	4.86	5.16	8.15	5.85
East Dummy	0.01	0.01	0.23	0.07
Calendar Year	0.39	0.45	0.51	0.45
May to July	0.39	0.38	0.36	0.38
Zip Codes	2,452	2,467	2,195	6,865
No. of Buildings	27,820	33,335	21,866	83,246

Notes: The table reports average values using the all building types in year 2009. Unemployment rate and purchasing power per household are computed at the zipcode level using data from RWI and microm (2019). Price of heating fuel is given in euro per kWh. East dummy indicates the share of buildings located in the following federal states: Berlin, Brandenburg, Mecklenburg-Vorpommern, Freistaat Sachsen, Sachsen-Anhalt, and Freistaat Thüringen. Calendar year reports the share of buildings that were treated with the January to December billing cycle. May to July reports the proportion of buildings that billing cycles starting in those months.

Table 3.14: Estimates of the Conditional Average Treatment Effects

Oil Units By Terciles of Unemployment Rate

Bill Start	*Dependent variable*: ln (kWh/m^2)			
	T1	T2	T3	Full
April to August	0.0055	0.0273*	0.0470***	0.0225**
	(0.011)	(0.011)	(0.014)	(0.007)
	T1	T2	T3	Full
February	-0.0249	0.0029	0.0076	-0.0084
	(0.017)	(0.017)	(0.022)	(0.011)
March	-0.0097	0.0060	0.0148	0.0018
	(0.018)	(0.017)	(0.023)	(0.011)
April	-0.0057	0.0223	0.0457*	0.0158
	(0.018)	(0.017)	(0.021)	(0.011)
May	0.0227	0.0476**	0.0680***	0.0430***
	(0.018)	(0.017)	(0.020)	(0.011)
June	0.0497**	0.0668***	0.0657***	0.0595***
	(0.017)	(0.016)	(0.019)	(0.010)
July	0.0290	0.0605***	0.0379	0.0439***
	(0.018)	(0.017)	(0.020)	(0.011)
August	0.0052	0.0339	0.0695**	0.0272*
	(0.018)	(0.018)	(0.024)	(0.012)
September	0.0264	0.0034	0.0086	0.0153
	(0.015)	(0.015)	(0.021)	(0.010)
October	-0.0065	0.0264*	0.0066	0.0092
	(0.011)	(0.011)	(0.014)	(0.007)
November	-0.0094	-0.0033	-0.0229	-0.0095
	(0.013)	(0.013)	(0.018)	(0.009)
December	-0.0288	-0.0076	0.0319	-0.0086
	(0.016)	(0.015)	(0.019)	(0.010)
Costs per kWh	-0.0118***	-0.0310***	-0.0582***	-0.0198**
	(0.002)	(0.004)	(0.011)	(0.007)
HDD 12 month sum	Y	Y	Y	Y
HDD 3 month sum	Y	Y	Y	Y
Year FE	Yes	Yes	Yes	Yes
# of Apts x PLZ FE	Yes	Yes	Yes	Yes
N	228,296	264,933	182,392	677,700
Adj R^2	0.281	0.268	0.359	0.304

Notes: Data on the unemployment rate was available from 2009 to 2017. The full sample in the last column covers all terciles for 2009 to 2017. The first row reports CATE when treatment group consists of non-heating months April to August and control group consists of September to March. For April to August, the pooled treatment group, the differences between the coefficients by terciles are not statistically significant in a regression with interactions between treatment and terciles. Using separate regressions, the rows below report estimates for each billing period, where the omitted month is January, the control month group. Standard errors clustered at the building level and robust to heteroskedasticity for all regressions. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.15: Heating vs. Non-Heating Months

Oil Buildings

Bill Start	*Dependent variable*: ln (kWh/m^2)			
	(1)	(2)	(3)	(4)
May to July	0.0414***	0.0416***		
	(0.00486)	(0.00488)		
April to August			0.0368***	0.0369***
			(0.00468)	(0.00469)
Costs per kWh	-0.0381***	-0.0361***	-0.0378***	-0.0358***
	(0.00627)	(0.00551)	(0.00616)	(0.00541)
HDD 12 month sum	Y	Y	Y	Y
Year FE	Yes	Yes	Yes	Yes
# of Apts X PLZ FE	Yes	Yes	Yes	Yes
Sample	All	Apts<11	All	Apts<11
N	326,338	309,930	362,210	344,790
Adj R^2	0.351	0.331	0.338	0.318

Notes: The full sample now excludes the calendar year billing period. The control or omitted group consists of buildings billed starting in September to December, February, and March. In the first two columns, I further exclude April and August from the sample. Robust standard errors clustered at the zip code level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.16: Year of Construction

Oil Buildings

			Building Code Regulation			
Bill Start	Pre-1919	1919–1977	1978–1983	1984–1994	1995–2001	2002+
Jan	1892	1964	1980	1990	1997	2004
Feb	1878	1961	1980	1991	1997	2005
Mar	1902	1962	1980	1991	1997	2003
Apr	1893	1962	1980	1990	1997	2005
May	1893	1962	1980	1990	1996	2004
June	1888	1965	1980	1989	1997	2003
July	1887	1963	1981	1989	1997	2004
Aug	1885	1964	1980	1990	1997	2003
Sept	1878	1961	1980	1990	1997	2003
Oct	1885	1961	1981	1990	1997	2004
Nov	1887	1964	1980	1990	1997	2003
Dec	1892	1962	1981	1990	1997	2003
All Bills	1891	1964	1980	1990	1997	2004
# of Buildings	3,257	25,074	4,014	6,328	2,679	297

Notes: The table reports average values calculated using information reported on energy performance certificates, observed from 2008 to 2018 for buildings using heating oil as the main fuel.

Table 3.17: Oil Units with Energy Performance Certificates

Calendar Year Versus Other Billing Cycles

Bill Start	*Dependent variable*: ln (kWh/m^2)				
	(1)	(2)	(3)	(4)	(5)
February	-0.025	-0.036	-0.037	-0.026	-0.049*
	(0.0205)	(0.0198)	(0.0197)	(0.0146)	(0.0244)
March	0.054**	0.054**	0.052**	0.045**	0.059*
	(0.0199)	(0.0190)	(0.0190)	(0.0151)	(0.0257)
April	0.014	0.010	0.009	0.024	0.007
	(0.0165)	(0.0160)	(0.0160)	(0.0128)	(0.0206)
May	0.057***	0.047**	0.046**	0.054***	0.051**
	(0.0149)	(0.0146)	(0.0146)	(0.0120)	(0.0186)
June	0.063***	0.046***	0.047***	0.048***	0.047**
	(0.0129)	(0.0127)	(0.0127)	(0.0108)	(0.0169)
July	0.045**	0.043**	0.043**	0.039***	0.057**
	(0.0138)	(0.0136)	(0.0136)	(0.0114)	(0.0186)
August	0.054**	0.046**	0.046**	0.034**	0.063*
	(0.0168)	(0.0166)	(0.0165)	(0.0132)	(0.0260)
September	0.006	-0.001	-0.001	0.020	0.008
	(0.0152)	(0.0149)	(0.0148)	(0.0121)	(0.0231)
October	-0.007	-0.009	-0.010	0.005	0.002
	(0.0119)	(0.0115)	(0.0115)	(0.0090)	(0.0162)
November	0.004	-0.005	-0.004	0.008	-0.006
	(0.0166)	(0.0158)	(0.0159)	(0.0134)	(0.0266)
December	-0.067***	-0.071***	-0.072***	-0.048**	-0.055*
	(0.0198)	(0.0186)	(0.0186)	(0.0149)	(0.0262)
Costs per kWh	-0.038***	-0.038***	-0.038***	-0.039***	-0.032***
	(0.0082)	(0.0083)	(0.0083)	(0.0082)	(0.0038)
Year of Construction			-0.0004***		
			(0.0001)		
Minimum EPC score				0.005***	
				(0.0001)	
2008 EPC score					0.004***
					(0.0001)
HDD 12 month sum	Y	Y	Y	Y	Y
HDD 3 month sum	Y	Y	Y	Y	Y
Year FE	Yes	Yes	Yes	Yes	Yes
# of Apts X PLZ FE	Yes	Yes	Yes	Yes	Yes
Building Code FE		Yes	Yes	Yes	Yes
N	315,298	315,298	315,298	315,298	129,703
Adj R^2	0.442	0.457	0.457	0.539	0.548

Notes: The control or omitted group consists of buildings with calendar year billing. Robust standard errors clustered at the building level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.18: Oil Units Constructed Before 1978

Calendar Year Versus Other Billing Cycles

Bill Start	*Dependent variable*: ln (kWh/m^2)				
	(1)	(2)	(3)	(4)	(5)
	All Types	2 HH	3 - 6 HH	7 - 12 HH	13+ HH
February	-0.034	0.041	-0.047	-0.060	-0.330***
	(0.0232)	(0.0436)	(0.0293)	(0.0792)	(0.0550)
March	0.056*	0.134**	0.066*	-0.133	-0.056
	(0.0245)	(0.0473)	(0.0314)	(0.0872)	(0.1246)
April	0.032	0.093	0.036	0.002	0.102
	(0.0195)	(0.0485)	(0.0247)	(0.0516)	(0.0774)
May	0.065***	0.125**	0.066**	0.088*	-0.008
	(0.0171)	(0.0452)	(0.0232)	(0.0399)	(0.0508)
June	0.051***	0.153***	0.049*	0.043	0.035
	(0.0149)	(0.0435)	(0.0207)	(0.0316)	(0.0444)
July	0.044**	0.114**	0.051*	0.043	-0.089
	(0.0165)	(0.0441)	(0.0223)	(0.0382)	(0.0675)
August	0.059**	0.125*	0.060*	0.071	-0.062
	(0.0208)	(0.0507)	(0.0263)	(0.0408)	(0.0902)
September	-0.018	0.090*	-0.038	-0.015	-0.034
	(0.0196)	(0.0439)	(0.0246)	(0.0435)	(0.1020)
October	-0.009	0.027	-0.001	-0.035	-0.225
	(0.0159)	(0.0303)	(0.0204)	(0.0403)	(0.1498)
November	-0.006	-0.086	0.027	-0.006	-0.162**
	(0.0221)	(0.0602)	(0.0270)	(0.0408)	(0.0543)
December	-0.063**	-0.118*	-0.049	-0.035	-0.035
	(0.0236)	(0.0496)	(0.0326)	(0.0435)	(0.0452)
Costs per kWh	-0.039***	-0.042***	-0.027***	-0.092***	-0.100***
	(0.0085)	(0.0004)	(0.0007)	(0.0056)	(0.0035)
HDD 12 month sum	Y	Y	Y	Y	Y
HDD 3 month sum	Y	Y	Y	Y	Y
Year FE	Yes	Yes	Yes	Yes	Yes
# of Apts X PLZ FE	Yes	Yes	Yes	Yes	Yes
N	209,141	25,717	110,145	41,293	31,986
Adj R^2	0.468	0.402	0.397	0.538	0.654

Notes: The control or omitted group consists of buildings with calendar year billing. Robust standard errors clustered at the building level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.19: Stuttgart and Munich

Oil Buildings

Bill Start	ln (kWh/m^2)			
	Stuttgart (ROR 810)		Munich (ROR 910)	
May to July	0.0574***	0.0529***	0.0577***	0.0581***
	(0.0111)	(0.0119)	(0.0166)	(0.0173)
HDD 12 month sum	Y	Y	Y	Y
Year FE	Yes	Yes	Yes	Yes
# of Apts X PLZ FE	Yes	Yes	Yes	Yes
Sample	All	Apts<7	All	Apts<7
N	36,157	27,933	32,597	25,480
Adj R^2	0.224	0.180	0.267	0.218

Notes: The control group consists of other billing cycles. The results are not sensitive to the exclusion of heating costs per kWh as a control variable. ROR stands for Raumordnungsregion (regional planning region). Robust standard errors clustered at the building level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.20: Sample Means – Oil Buildings Built Pre-1978

	Panel A: Year of Construction/Renovation						
	Year Built	Heater	Roof	Loft	Outer Wall	Windows	Basement
Calendar Year	1955.81	1996.12	1974.94	1968.35	1965.63	1976.99	1960.84
(SD)	(29.35)	(12.09)	(26.94)	(27.53)	(27.51)	(25.41)	(26.46)
N	14,164	12,451	5,163	7,473	8,360	6,303	9,373
May to July	1956.33	1995.49	1979.76	1969.50	1966.16	1982.91	1960.61
(SD)	(30.99)	(12.50)	(26.90)	(28.13)	(29.02)	(29.66)	(27.62)
N	10,554	8,878	3,257	5,089	5,850	4,081	6,738
	Panel B: WSVO 1995 (=1 if meets standards)						
	Overall	Heater	Roof	Loft	Outer Wall	Windows	Basement
Calendar Year	1.299	0.611	0.326	0.343	0.196	0.360	0.074
(SD)	(1.506)	(0.488)	(0.469)	(0.475)	(0.397)	(0.480)	(0.262)
N	5,741	12,451	5,741	5,741	5,741	5,741	5,741
May to July	1.705	0.599	0.425	0.438	0.239	0.522	0.081
(SD)	(1.471)	(0.490)	(0.494)	(0.496)	(0.427)	(0.500)	(0.272)
N	3,584	8,878	3,584	3,584	3,584	3,584	3,584

Notes: Standard deviations in parentheses. "Overall" indicates the number of building components (roof, loft ceiling, windows, outer wall, and basement ceiling) that meet thermal efficiency standards under WSVO 1995 building codes. This information was only available from energy performance certificates issued from 2014 to 2019.

Table 3.21: Differences in Energy Efficiency Investments

Oil Buildings Built Before 1978

Bill Start	*Dependent variable*: WSVO 1995 Standard						
	Overall	Heater	Roof	Loft	Outer Wall	Windows	Basement
May to July	0.231***	-0.00262	0.0596***	0.0192	0.0546***	0.0917***	0.00560
	(0.0435)	(0.0123)	(0.0151)	(0.0120)	(0.0150)	(0.0144)	(0.00789)
Year Built	-0.0010	-0.0001	-0.0007*	0.0001	-0.0006*	0.0004	-0.0001
	(0.0009)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Year of EPC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of Apts FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PLZ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,968	9,183	7,968	7,968	7,968	7,968	7,968
Adj R^2	0.189	0.070	0.135	0.099	0.124	0.173	0.079

Notes: The omitted billing month is January (calendar year billing), the control group. Standard errors clustered at the zip code level. Data is limited to energy performance certificates issued 2014 to 2019. Inclusion of controls such as heating costs (total bill) and total living space does not change the results in the table. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.22: Natural Gas Building with Energy Performance Certificate

Calendar Year Versus Other Billing Cycles

Bill Start	*Dependent variable*: ln (kWh/m^2)				
	(1)	(2)	(3)	(4)	(5)
February	0.077***	0.061***	0.019	0.019	0.012
	(0.0076)	(0.0125)	(0.0112)	(0.0112)	(0.0089)
March	0.078***	0.055***	0.021	0.021	0.009
	(0.0080)	(0.0131)	(0.0117)	(0.0117)	(0.0094)
April	0.079***	0.067***	0.039***	0.039***	0.050***
	(0.0082)	(0.0114)	(0.0104)	(0.0104)	(0.0084)
May	0.083***	0.079***	0.038***	0.038***	0.042***
	(0.0086)	(0.0118)	(0.0107)	(0.0107)	(0.0090)
June	0.128***	0.117***	0.045***	0.046***	0.042***
	(0.0080)	(0.0106)	(0.0098)	(0.0098)	(0.0085)
July	0.107***	0.104***	0.052***	0.052***	0.044***
	(0.0081)	(0.0108)	(0.0099)	(0.0099)	(0.0085)
August	0.083***	0.094***	0.052***	0.053***	0.041***
	(0.0104)	(0.0145)	(0.0133)	(0.0133)	(0.0105)
September	0.065***	0.061***	0.020	0.020	0.022*
	(0.0085)	(0.0130)	(0.0117)	(0.0117)	(0.0094)
October	0.063***	0.042***	0.004	0.004	0.004
	(0.0052)	(0.0080)	(0.0073)	(0.0073)	(0.0058)
November	0.050***	0.040***	0.010	0.010	0.013*
	(0.0059)	(0.0093)	(0.0084)	(0.0084)	(0.0064)
December	0.038***	0.029**	0.005	0.004	-0.009
	(0.0066)	(0.0108)	(0.0097)	(0.0097)	(0.0077)
Costs per kWh	-0.000*	-0.003***	-0.003***	-0.003***	-0.003***
	(0.0001)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Year of Construction				-0.0001*	
				(0.0001)	
Minimum EPC score					0.005***
					(0.0002)
HDD 12 month sum	Y	Y	Y	Y	Y
HDD 3 month sum	Y	Y	Y	Y	Y
Year FE	Yes	Yes	Yes	Yes	Yes
# of Apts X PLZ FE	Yes	Yes	Yes	Yes	Yes
Building Code FE			Yes	Yes	Yes
Sample	All	EPC	EPC	EPC	EPC
N	1,605,802	752,629	752,629	752,629	752,629
Adj R^2	0.314	0.434	0.495	0.495	0.591

Notes: The control or omitted group consists of buildings with calendar year billing. Robust standard errors clustered at the building level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.23: District Heating Buildings with Energy Performance Certificates

Calendar Year Versus Other Billing Cycles

Bill Start	*Dependent variable*: ln (kWh/m^2)				
	(1)	(2)	(3)	(4)	(5)
May to July	0.080***	0.090***	0.074**	0.074**	0.074**
	(0.0179)	(0.0261)	(0.0257)	(0.0257)	(0.0249)
Costs per kWh	-0.000**	-0.002**	-0.002**	-0.002**	-0.002**
	(0.0001)	(0.0006)	(0.0006)	(0.0006)	(0.0007)
Year of Construction				0.000	
				(0.0002)	
Minimum EPC score					0.006***
					(0.0002)
HDD 12 month sum	Y	Y	Y	Y	Y
Year FE	Yes	Yes	Yes	Yes	Yes
# of Apts X PLZ FE	Yes	Yes	Yes	Yes	Yes
Building Code FE			Yes	Yes	Yes
Sample	All	EPC	EPC	EPC	EPC
N	256,343	146,393	146,393	146,393	146,383
Adj R^2	0.572	0.616	0.619	0.619	0.627

Notes: The control or omitted group consists of buildings with calendar year billing. Robust standard errors clustered at the building level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.24: Buildings with WSVO 1995 Standards

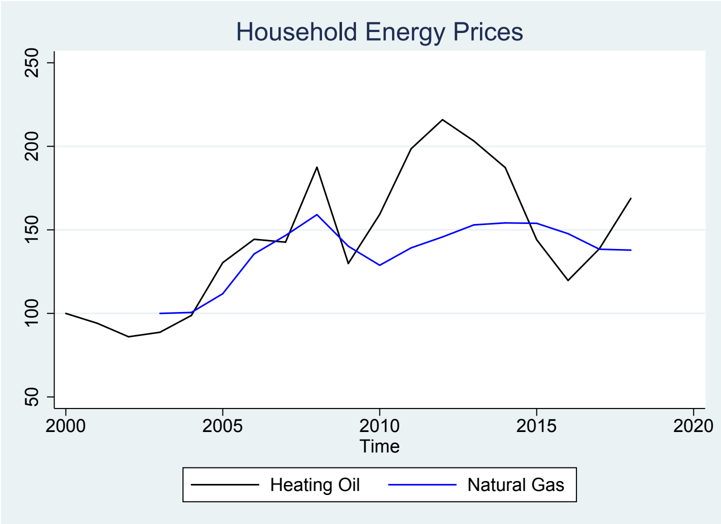
Calendar Year Versus Non-Heating Months

Bill Start	ln (kWh/m^2)		
	(1)	(2)	(3)
May to July	0.0877**	0.0844**	0.0920**
	(0.0334)	(0.0312)	(0.0306)
Costs per kWh	-0.0740***	-0.0745***	-0.0827***
	(0.0022)	(0.0019)	(0.0224)
HDD 12 month sum	Y	Y	Y
HDD 3 month sum	Y	Y	Y
Year of Construction		Y	Y
Heat System Year		Y	Y
Year FE	Yes	Yes	Yes
# of Apts X PLZ FE	Yes	Yes	Yes
Building Code FE		Yes	Yes
Fuel Type FE			Yes
Fuel Type	–Natural Gas–		All
N	101,540	101,483	133,445
Adj R^2	0.658	0.677	0.680

Notes: The control or omitted group consists of buildings with calendar year billing. "All" fuel types refers to mineral oil, natural gas H, and district heating. Robust standard errors clustered at the building level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

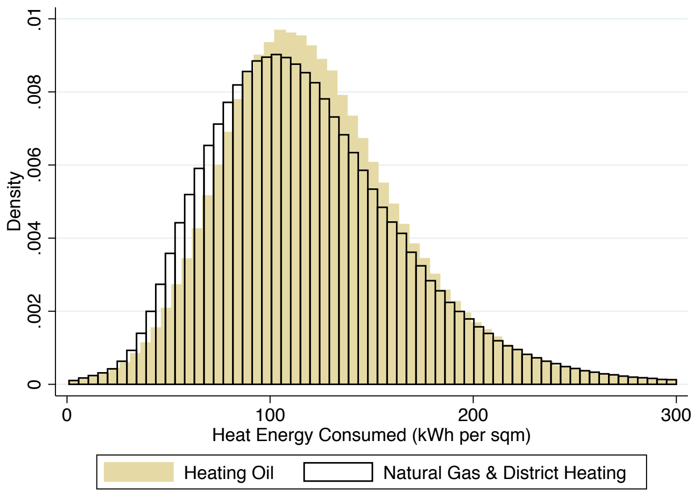
3.12 Appendix

Figure 3.1: Evolution of Heating Fuel Prices in Germany



Notes: The heating oil series presents annual consumer prices for light heating oil (for consumption of 5000 liters) in Euro cents per liter and natural gas series presents annual averages of biannual household prices in Euros per gigajoule. Due to data limitations, the natural gas price index is calculated using a combination of two different time series: (1) 2003 to 2007 price data applies to consumption class between 20 and 200 GJ and (2) 2008 to 2018 price data applies to consumption of 83.70 GJ. Both price series include all taxes and fees. For plotting, the raw data were indexed: heating oil (2000=100) and natural gas (2003=100). Sources: Mineralöl Wirtschaftsverband e.V. for leichtes Heizöl and Eurostat Datenbank for Preise Gas für Haushaltskunde.

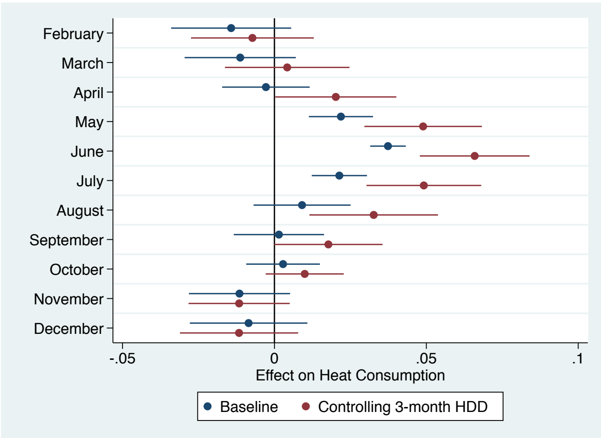
Figure 3.2: Distribution of Heat Demand



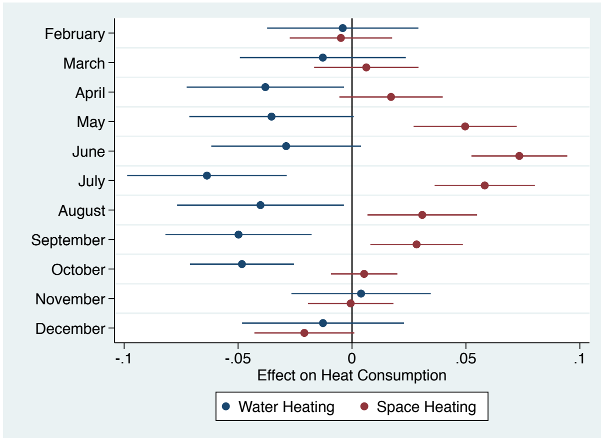
Notes: The histogram presents the distribution of annual heat energy consumed, limited to less than 300 kWh per square meter.

Figure 3.3: Rate of Overconsumption

Plot A



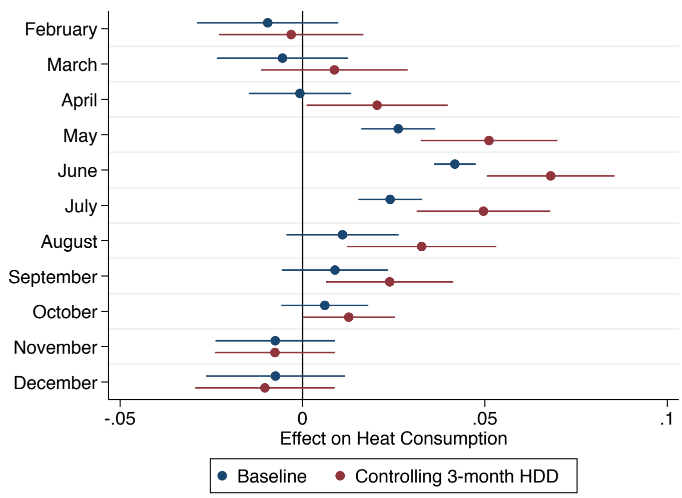
Plot B



Notes on Plot B: Graph shows that bills that are settled during non-usage months (May to September) are subject to over-consumption, relative to the calendar year billing cycle. 95% confidence intervals provided. Estimates for bills ending in May, June, and July are highly precise. Controlling for differences in the annual sum of heating degree days in the first 3 months post-billing strengthens the pattern.

Notes on Plot B: Heating bills cover costs incurred for water heating, in addition to space heating. Residential demand for fuel energy to heat water is less seasonal than that for space heating. Graph shows that HHs that are indeed paying attention to bills during the summer months adjust (disproportionately) the amount of energy they consume for water heating. 95% confidence intervals provided.

Figure 3.4: Trimmed Dependent Variable



Notes: The graph plots the treatment effect coefficients in Plot A of Figure 3.3, after discarding heating bills that report heat demand greater than or equal to 300 kWh per square meter (approximately 0.7% of the observations) .

Chapter 4

On Heat Demand and the Distribution of Energy Efficiency

4.1 Introduction

Residential heating continues to be primarily powered with fossil-fuels[1] and accounts for one-fifth of the final energy consumed in Germany (BMWi, 2019). Energy-efficiency programs are increasingly advocated as a key climate policy instrument for decarbonizing the building sector – both to reduce energy bills and mitigate climate damaging carbon emissions. However, evaluations have shown that actual savings realized from energy-efficiency programs seldom achieve the level of energy savings that are predicted using ex-ante engineering models (Fowlie et al. 2018, Allcott and Greenstone 2017).

Moreover, increasingly warmer heating seasons in Germany are prolonging the already long pay-back periods for energy-efficiency investments in the housing sector. It has thus become all the more important to target energy-efficiency funds and programs to homes that have the highest potential for energy-efficiency improvements, keeping in mind that energy savings may fall short of expected returns (Christensen et al. 2020, Giraudet et al. 2018).

Coupled with increasing energy efficiency, investments in housing may also have the additional objective to contribute to equity such that the costs and benefits from retrofit programs are allocated progressively across income groups (Bento, 2013). Although energy efficiency measures targeting the building sector play an increasing role in achieving GHG emission reductions globally, evaluations of policy instruments such as building

[1] 81% of final energy consumed for space heating was produced using natural gas, heating oil, district heating, and coal (AG Energiebilanzen e.V. 2018).

codes, retrofit programs, or energy performance certificates seldom take into account the long-term distribution of energy-savings achieved.

A few exceptional studies aim to cover this gap in the literature. Jacobsen (2019) shows that financial incentives such as tax credits for energy-efficient appliances were more concentrated for higher-income households. McCoy and Kotsch (2020) investigate the returns to energy-efficiency investments by income group and find that the poorer households experience lower energy savings both in the short- and long-run. Similarly, Bruegge et al. (2019) find that building codes in California led to energy-savings for the lower income groups, but this was due to decrease in square footage rather than improvements in building energy-efficiency attributes.

We add to this literature on the distributional impacts of energy policies in the residential building sector. Here we take a long-term perspective and assess the net outcomes of major policy efforts (building codes, tax incentives, and retrofit programs) that have already take place in Germany and come to a more nuanced conclusion. In line with the previous literature, the distribution of energy-efficiency is regressive[2] in the West of Germany. However, the poorest regions of Germany, the states in the East benefit from both the use of less carbon-intensive heating fuel type and energy-efficient buildings.

The contribution of this paper is three-fold.

First, we provide a methodological improvement over consumption-based energy performance ratings to measure energy-efficiency of buildings. We make use of heating bills for a large sample of the existing building stock in Germany and temperature data from 204 weather stations to underpin the causal response heat energy demand to short-run fluctuations in the total annual sum of heating degree days. Using this building-level response of heat energy consumption to temperature as an overall measure of energy-efficiency, we find that buildings in Bavaria and Baden Württermberg outperform those from all other states.

Second, we document that temperature change is an increasingly dominant factor in explaining the observed decline in heat energy use by the German housing sector in the last decade, and discuss potential implications for energy efficiency investment incentives. Global surface temperatures have been rising steadily relative to historical average temperatures (NASA). Germany, in particular, experienced an unwavering increase in average temperatures in the past decade from 2010 to 2019[3]. Unsurprisingly, the heat-

[2]By regressive, we mean that zipcodes that are associated with low unemployment rates or high incomes are home to a disproportionately higher share of energy-efficient buildings.

[3]The German Weather Service (DWD) reported 2018 to be the warmest year in its 138-year temperature records, and 2019 tied with 2014 were the second-warmest years in German history.

ing sector is particularly affected by global warming because the demand for energy to heat homes falls, cetris paribus. We quantify the fall in heat energy demand for heating due to climate change in the last decade, and thus the weakening financial incentives for homeowners to invest in thermal-efficiency of the existing building stock.

Third, we provide new evidence on the distribution of realized energy efficiency outcomes. We investigate comprehensively the main drivers of the heterogeneous response to temperature shocks, allowing us to gain insight into the mechanisms driving estimated differences in energy-efficiency. To this end, we employ machine learning to explore all observable dimensions in a systematic manner. We shed light on the heterogeneity in outcomes by socioeconomic disparities, in particular the East-West divide in Germany. By focusing on the existing building stock with average year of construction in 1967, we also circumvent the problem of measuring energy-efficiency outcomes in a short-time frame as highlighted by Kotchen (2017).

Given that the retrofit rate of existing buildings has been abysmally low over the last two decades (Ray and Sunikka-Blank, 2013), the main candidate to have improved the energy-performance of buildings are building codes, that have been rising in stringency since 1978, when they were first introduced. We do not quantify the causal link in this paper, but using precise measures we provide evidence on the strong negative association between realized heat energy-requirements of buildings and the stringency of federally-enforced building codes in Germany.

Our results provide insight into potential distributional effects of climate policy targeting the residential sector in Germany. Assuming that all carbon-costs are passed on to end-users of heat energy, the findings in this paper suggest that a carbon price on heating fuel supply is likely to improve distributional outcomes in Germany. This is in large part because buildings located in zip codes at the lower end of the unemployment distribution and richest states of Bavaria and Baden Württemberg have a significantly higher share of homes using heating oil, which is more carbon-intensive than natural gas (see Figure 4.1 and Tables 4.9). At the same time, buildings connected to district heating are located in the East and the upper end of the unemployment distribution – regions marked with poor socioeconomic status.

Compounding these regional differences in the carbon-intensity of heating fuel used is the distribution of the energy-efficiency attributes of buildings. We show that although the newer and more energy-efficient building are located in the South of Germany, buildings in the poorest East regions of Germany are surprisingly energy-efficient, owing to larger buildings, renovation efforts, and efficient construction that took place post-reunification in the between 1990 and 2001. For instance, we document that the older building stock (built before 1975) in the East of Germany is significantly more energy-efficient than the comparable group in the West. At the same time, East buildings are on average larger than those in the West of Germany and this further associated with less energy per square meter of living space for each heating degree day.

The next section provides some context for the analysis via a description of the residential building sector in Germany and how energy ratings on energy performance certificates are calculated. Section 4.3 describes the data used in this paper. Section 4.4 reports on the underlying trends in heat demand and heating degree days. Section 4.5 explains the identification strategy and estimates the average response of energy demand to temperature. Section 4.6 considers the heterogeneous treatment responses. Section 4.7 offers a forest-based machine learning method to understand the sources and corresponding importance of heterogeneous treatment effects. Section 4.8 discusses policy implications and conclusions.

4.2 Institutional Setting

4.2.1 National Context

Space heating accounted for approximately 70% of the final energy consumed by the private housing sector in 2017, and residential heating is almost one-fifth of Germany's total final energy consumption (AGEB 2018 and BMWi 2019).

The German Federal Statistical office conducts a special census survey every four years to report on the current housing situation in Germany. Based on the 2014 Microcensus results (Destatis 2016), 50% of the rented German housing units were using natural gas for home heating, 22% were using district heating, another 19% using heating oil, and only about 2% using electricity. These figures were approximately the same in the 2010 and 2018 Microcensus reports. In this paper, we study buildings that were using natural gas (high calorific or low calorific), district heating, and mineral oil to heat their homes from 2008 to 2018. This amounts to excluding those buildings using LPG, pellets, electricity, wood, coal, brown coal, steam, and coke as main heat fuel energy.

Table 4.1 shows the distribution of buildings represented in the sample by fuel type and number of housing units. Compared to the 2014 Microcensus survey results, district heating as the main fuel type is under-represented in the sample, while natural gas and heating oil are both over-represented. In the billing data sample, we observe all residential building types except those with only one housing unit – single-family homes. The Microcensus survey in 2014 reports that more than two-thirds of German households were living in buildings with 2 or more apartments or housing units, however. Relative to the population, the sample has a higher share of buildings with 3 to 6 apartment units and large housing blocks (with 13 or more apartments). At the same, building type with 7 to 12 apartments are underrepresented.

Table 4.2 shows the regional distribution of the full sample. The sample used has regional coverage that mirrors how the population of buildings is distributed (Destatis 2016). In total, we observe buildings from 7769 zip codes, in all sixteen Federal States of Germany.

Figure 4.1 shows the distribution of main fuel types used by buildings in the sample by terciles of the unemployment rate. In the Appendix (Tables 4.9 and 4.10), by comparing the data sample with statistics from the Microcensus 2010 for owner-occupied and rented buildings with 2 or more housing units, we show some evidence that this distribution is likely representative of the population.

4.2.2 Problem with Energy Performance Certificates

In this section, we explain why energy performance scores that use past consumption to measure the energy-efficiency rating of buildings are inadequate as measures of energy-efficiency. We start with a brief description of how energy performance scores based on consumption (as opposed to theoretical energy-requirements using engineering calculations) are calculated:

In accordance with the official guidelines[4], energy performance ratings on consumption-based ("Verbrauchsausweis") energy performance certificates (EPC) are calculated using building-level consumption in the past three years (in kWh per square meter of usable living space) and a climate factor to adjust for weather and climate differences. The climate factor anchors "typical climate" to the reference location of Potsdam, taking the average of annual heating degree days recorded from 1995 to 2012. Thus, in any given year if the local weather is warmer (colder) than "typical climate" in Potsdam, then consumption is adjusted upwards (downwards) accordingly by multiplying the annual consumption in kWh in square meters by the ratio of the annual sum total of heating degree days recorded in Potsdam and at the local weather station. This allows buildings nation-wide to be compared to each other in terms of energy performance.

Using this method, however, does not give a transparent rating of the heat energy requirements of a building because the performance scores are not independent of the behaviour of tenants vs. residents, energy prices by fuel type, and other demographic and socio-economic factors. More importantly, correcting consumption for temperature and climate

[4]"Bekanntmachung der Regeln für Energieverbrauchswerte im Wohngebäudebestand Vom 7. April 2015"

change to determine the "true" trend in heat demand may require much more than multiplicative climate factors. It requires us to consider heterogeneous response to changes in temperature that vary by regions, income, tastes, building attributes, and other energy-efficiency parameters. In comparison, the energy demand certificate ("Bedarfsausweis") is a more objective measure because it is the theoretical energy-requirement of a building.

In absence of sufficient data on energy-demand certificates for buildings, it is useful to consider how consumption responds to temperature as an improvement over consumption-based energy performance scores on EPCs. As we will show in the results sections, the strong response of heat energy demand to the decline in average temperatures allows us to precisely estimate the energy performance of the existing building stock in a fixed-effects framework and detect even very small differences in energy efficiency between buildings and regions using machine learning.

4.3 Data

The analysis in this paper is based on data combined from three sources: (1) data on building-level heating bills and energy performance certificates from a leading energy-metering company, (2) weather station data from the German Weather Service (Deutscher Wetterdienst), and (3) socio-demographic data from RWI-GEO-GRID (Breidenbach and Eilers, 2018).

4.3.1 Heating Bills

The primary data used come from a large panel of building-level heating bills for 420,573 residential buildings (3,215,800 bills) in Germany, with 12-month billing cycles that start during January 2008 to June 2018. 12-month billing means that all heating bills are for either 365 or 366 days, but the billing start and end dates vary.

The billing dataset contains information on the actual units of energy consumed for space heating and water heating, along with yearly costs incurred. The billing data also contains important building characteristics that help determine the energy requirements of buildings: living space (in square meters), building size (in number of apartments), location by zip code, heating fuel type.

The main dependent variable is calculated as the annual quantity of heating energy consumed in relation to the per square meter heated living space of a building. This took several steps: first, building-specific consumption values are limited to the amounts of energy used for heating space (excluding warm water). Second, the consumption value is multiplied by the heating value corresponding to the buildingâs energy fuel type, giving us the absolute heating energy consumption in kilowatt-hours (kWh) for a building during the billing period. Fourth, we divide total kilowatt-hours consumed by the amount of heated living space in the building. The units are therefore, kilowatt-hours per square meter of heated living space per year (kWh/sqm).

We calculate heating costs used for the heating energy consumed by first deducting costs of heating water from the total energy costs reported in each bill. Then dividing total costs for space heating by the amount of heated living space in the building gives us the cost per kWh of heat energy billed.

To create my estimation sample, we only consider heating bills from buildings that use either natural gas, heating oil, or district heating as the main fuel type, which is 98 percent of all buildings observed. We trim the sample further by removing the top and bottom 1% tails from the distribution of heat energy consumption, used as the main dependent variable: such that kWh consumption is above 30 kWh/sqm and below 400 kWh/sqm of heated living space.

Finally, we only consider only those buildings observed at least two times in the (unbalanced) panel. After these steps, the full sample consists of 384,223 buildings with a total of 3,030,063 observed heating bills. On average we observe a building 9 times, minimum number of 2 times, and a maximum number of 11 times.

4.3.2 Energy Performance Certificates

For about 40 percent of the buildings, we observe energy performance certificates issued from 2008 to 2019 that give us important measures for the thermal-efficiency attributes of the buildings, including the energy performance score, construction year of the building, year (or renewal year) of the heating system, roof, loft ceiling, exterior wall, windows, and basement ceiling. For energy performance certificates issued from 2014 to 2019 (about 20% of the sample), I further observe whether individual building components meet thermal insulation standards set out in the national thermal insulation ordinance from 1995 (Wärmeschutzverordnung 1995 or WSVO 1995).

4.3.3 Supplementary Data

We supplement the energy-related data with data from local weather stations collected by the German meteorological service (Deutscher Wetterdienst). To construct variables that capture the number heating degree days, we find the nearest available weather station to 8303 geocoded zip codes of Germany, provided that there is not more than one consecutive daily observation record missing for mean temperature for each weather station from 2003 to 2019. For the few missing values, we impute using the average of mean temperatures recorded for the previous and next day. This procedure amounts to using daily mean temperatures from 204 weather stations scattered across Germany to calculate heating degree days corresponding to each billing month and cycle.

The socio-economic variables used in this paper are the unemployment rate, housing density, and the purchasing power[5] per household computed using high-resolution grid level (1x1 kilometer cells) data (RWI and microm 2020, Breidenbach and Eilers 2018), aggregated to the zip code level and matched to the billing sample. The data is available for 2005 and 2009 to 2017.

4.3.4 Descriptive Statistics

In this section, we describe aggregate trends in key variables observed from the data. Table 4.3 presents summary statistics for the full sample at the yearly level for important determinants of heat energy demand. We report averages for the East of Germany in parentheses.

Based on this table, there is evidence that financial incentives for heat energy-efficiency investments have been falling. Along with warmer heating seasons, costs of heating fuel (cents per kWh) have not risen significantly, resulting in declining annual heating expenditures per square meter (energy use x price) since 2008. Meanwhile, information from the sample of energy performance certificates suggests that thermal-efficiency and insulation standards have not increased noticeably for the existing housing stock.

These trends are also true for the East of Germany. However, there is a noteworthy exception. Although the buildings in the East of Germany are on average older, a higher share of buildings (about half) observed with energy performance certificates from 2014 to 2019 met thermal insulation standards set out in WSVO 1995.

To make this distinction clearer, we split up the sample to those buildings built prior to 1995 and those built starting 1995, and then look at the shares that meet the WSVO 1995 standard or not. Figure 4.2 shows that a significantly higher share of the East building stock built before 1995 meet thermal insulation standards under WSVO 1995. In order to meet the WSVO 1995 standards, buildings built before 1995 likely underwent higher rates of retrofitting. At the same time, we do not detect a noticeable share of buildings built 1995 onwards that were in non-compliance with the building regulation. In Figure 4.14,

[5] A measure of disposable income – "[t]he variable purchasing power reflects the household income. It comprises information on labour supply, capital wealth, rental and leasing income minus taxes and social security contributions, including social transfers such as unemployment benefits, child-allowances and pensions." (Breidenbach and Eilers, 2018)

we further graph the differences in certification rates by individual building component.

What may explain this stark difference between the East and the rest of Germany? Since reunification of Germany in 1990, there had been a concerted political and financial effort (via subsidies for renovation and new construction) to improve the quality of the housing stock in East, at least until 2001 (Weiß and Michelsen, 2011). Using identical data on energy performance certificates, Singhal and Stede (2019) document that the thermal retrofit rate was significantly higher for East German buildings during the 90s until 2001. Renovation investments made in the East housing sector in the 1990s are likely driving the improved energy performance of the building stock we observe today.

4.4 Trends in Heat Demand

Figure 4.3 plots yearly averages for the two main variables of interest in this paper: local heating degree days and kWh per sqm of heat energy consumed by buildings. We demonstrate that the correlation between average heat energy demand and annual sum total of heating degree days increased from 2003 - 2012 to 2008 - 2018.

It is further noteworthy that the aggregated time series from 2008 to 2018 exhibit near identical movements over time. Although the downward linear trends (see fitted values) are similar, heat energy demand appears to be decreasing at a slightly faster rate than heating degree days.

Figure 4.3 suggests that (1) temperature plays an increasingly dominant role in determining heat energy demand, (2) during 2008 - 2018, renovations, demographic changes, and economic factors such as prices played a smaller role (at least on net) in predicting heat energy demand. This is strong suggestive evidence that policies targeting CO_2 emission reductions via technical efficiency of the building sector may not have had the desired effect for the sample population.

Moreover, thermal retrofitting of the existing housing stock is widely considered among German policymakers to be cost-effective in reducing heat energy consumption (Ray and Sunikka-Blank 2013). But given the declining trend in heating degree days and thus heat demand, the pay-back period for thermal-efficiency investments continues to get longer, and we expect fewer (rather than more) renovation projects to be economically feasible due to climate change. In short, the potential for cost-efficient carbon savings from residential energy efficiency have been declining in the last decade. It remains an empirical question, however, how the currently falling financial incentives for a more energy-efficient housing stock will be altered in response to a carbon-pricing scheme on the residential heating sector.

4.5 Temperature Response of Heat Demand

The primary aim of this paper is use precise estimates of the effect of temperature fluctuations on heat energy consumption to understand the heat energy requirements of the existing building stock. As discussed already, the estimation sample period covers 8 of the 10 warmest years ever recorded in Germany's history, lending us high statistical power in estimating the response of energy demand to temperature.

4.5.1 Identification

We seek to isolate the underlying heat-energy requirements (a measure of energy efficiency) at the building level by estimating the direct response of building-level heat demand to temperature variability. The main advantage of the empirical approach is that we control for all time-invariant characteristics of buildings that could affect heat demand of buildings in response to temperature. Furthermore, we can control for important time-varying observables that determine heat demand and are correlated with energy-efficiency.

We use the following baseline regression to estimate the average response of heat energy requirements to temperature:

$$y_{is} = \alpha + \beta \text{HDD}_{is} + \gamma_i + \phi_s + \lambda_t + \kappa_f + \epsilon_{is} \tag{4.1}$$

where y_{is} denotes annual energy units consumed (kWh) per sqm by building i with billing cycle starting in year s.

- HDD captures the numbers of heating degree days in any given 12-month billing period, calculated as the total sum of differences between the daily mean temperature and the heating threshold of 15°C on days with recorded mean temperatures less than 15°C. Succinctly,

$$\text{HDD} = \sum_{d=1}^{365/366} (T_H - t_d) \times 1(t_d < T_H) \tag{4.2}$$

  We considered different heating thresholds of T_H from 10°C to 20°C and chose the heating threshold of 15°C because it minimizes Root Mean Squared Error (RMSE).

- γ_i captures the building-level fixed characteristics such as vintage, building type, number of apartments, number of floors, quality of building components associated with thermal insulation, aggregate characteristics of residents, ownership status, and fixed-factors related to geographic location.

- ϕ_s are fixed effects for the year (s) in which annual billing cycle starts. This controls for any aggregate time trend in consumer behavior or preferences for heating, influenced by gradually decreasing heating degree days, measured for each building's billing period.
- λ_t are fixed effects for the year (t) in which the majority of billing took place. Note that $s \neq t$ for bills starting late in the second half of the year (August to December). This may capture year-specific economic shocks that are common to all buildings.
- σ_f are fixed effects for the fuel type, which may or not be fully captured by building fixed effects.
- ϵ_{is} the error term, clustered at the zip code level.

The coefficient of interest is β on HDD. β reports the change in annual kWh of heat energy demand per square meter in response to a unit increase in the annual sum total of heating degree days, after controlling for fixed factors associated with buildings, residents, and geographic location.

4.5.2 Results

Table 4.4 presents results for the full estimation sample. We present four variations of the baseline regression model and consistently estimate that heat energy consumed by a building per annum fell on average by 3.1 kWh/m^2 of heated living space in response to a decrease of 100 degree days in the annual sum total of local heating degree days (with mean outside temperature below 15 degree Celsius).

After controlling for fixed characteristics of buildings, the results generally confirm the exogenous nature of short-run temperature changes with respect to important determinants of heat energy demand. In the first column, after controlling for fixed characteristics of buildings and yearly shocks common to all homes in their respective billing periods, we arrive at a coefficient that is more or less insensitive to more conservative specifications. In the second column, we add fixed effects for majority billing year interacted with fuel type, which capture fuel price shocks. In the third column, we add time-varying covariates at the building level (price per kWh of energy, building size, and average apartment size) and zip code level (unemployment rate, purchasing power per household, and building density). Finally, in the fourth column we control for any time-varying factors at the zip-code level that may affect building-level energy efficiency. We also considered other weather parameters and show that the average estimate is robust to the inclusion of precipitation and relative humidity (see Appendix Table 4.12).

Holding a slew of factors constant, the average heat energy requirement of buildings is approximately 0.031 kWh per sqm for each heating degree day – which corresponds to an average yearly energy requirement of 79.7 kWh per sqm per building, assuming linearity in temperature response and total heating degree days of 2414, which is the average 12-month sum of heating degree days recorded at 204 weather stations in Germany from 2003 to 2018[6]. Compared to "typical" climate, the decline in the annual sum of heating degree days measured in the last five years (2014 to 2018) translates this estimate to an average reduction of 8 percent in annual heat energy demand. For a household living in a 100 square meter apartment, expenses in 2018 for space heating fell by approximately 60 euros due to change in climate (HDD relative to "typical").

4.5.3 Heat Demand Adjusted for HDD

The main disadvantage of the method outlined above is that we only consider the linear response of energy demand to changes in annual heating degree days. In the appendix, we considered annual sum of heating degree days in distinct temperature bins below the heating threshold of 15°C for each 12-month billing period. This allowed us to flexibly detect any non-linear response of building-level heat demand to changes in small versus large changes in local weather conditions (see Table 4.11). The results are largely consistent – for temperatures lower than the heating threshold, every 1 °C decrease in temperature in colder temperature bins require relatively more heat energy. The coefficient on "HDD if (°C < -5)" is significantly lower than what we expect. This is driven by the fact that observations from buildings in the East are over-represented in the coldest temperature bin and buildings in the East are on average more energy-efficient.

Using this more precise specification, which controls for the non-linear and heterogeneous response of heat energy consumption to temperature variation, we show how heat demand from the building sample has evolved since 2008. Figure 4.4 shows that heat demand was declining until 2014, after which the trend is ambiguous, given the wide confidence intervals. On average, the estimates suggest that heat energy demand has plateaued.

4.6 Effect Heterogeneity

Now we go beyond estimating the average treatment effects. We expect there to exist considerable heterogeneity in temperature response, not least because newer buildings

[6]The values are calculated by the author using daily observations from 20030101 to 20181231 at 204 nearest weather stations to 8303 zipcodes in Germany. In the mapping used, average distance between zip code and nearest weather station is 18.3 km, with standard deviation of 10.4 km, minimum and maximum distance of 0.076 km and 59.86 km respectively. Source: Deutscher Wetterdienst (DWD)

were subject to stricter building energy codes. In this section, we explore which subgroups of buildings response less or more to temperature, and thus seek to uncover the heterogeneity in heat energy requirements of the existing building stock. We consider those variables that are most likely related to treatment effect heterogeneity: year of construction, size of building, the unemployment rate, and federal states with the West of Germany.

4.6.1 Building Vintage

To start, we consider energy-efficiency outcomes by building vintage grouped such that they correspond to different energy efficiency codes. Energy efficiency regulation in Germany has largely taken the form of building codes, that define the building-aggregate maximum annual energy requirement per square meter of living space for newly constructed homes. Table 4.5 summarizes the time development of building codes in Germany. The Heat Insulation Ordinance was first introduced in 1978, amended and made progressively more stringent in 1984 and 1995. It was replaced by the Energy Saving Ordinance in 2002 and subsequently amended in 2009. Note that there were no minimum energy standards for buildings built before 1978.

In Table 4.6, we estimate the response of energy requirements to temperature separately for buildings in the West and East of Germany[7]. For the West, the average heating requirement per heating degree day is monotonically decreasing with each successive revision (tightening) of building codes, until 2009. For instance, the difference in the average temperature response between buildings built in 1984–1994 and those built in 1995-2001 is 32%. Nevertheless, compared to buildings built from 2009 onwards, buildings built before 1978 are on average less energy-efficient by a factor of 2.

This decreasing pattern is less clear, however, when we consider only the buildings located in the East of Germany. These results are a strong indication that other factors such as renovations targeting energy-efficiency of older buildings, other building attributes, or state-level policy efforts could be important in explaining the differences in energy requirements of buildings in the East.

Comparing across the regions, the coefficients in the first column shows that that buildings built before 1984 in the East perform comparatively well, while the energy-requirements are lower for buildings built from 1995 in the West. Interestingly, pre-1978 (before building regulation) buildings in the East are significantly older, but on average demand less heat energy per heating degree Celsius.

[7]East is located in the following federal states: Berlin, Brandenburg, Mecklenburg-Vorpommern, Freistaat Sachsen, Sachsen-Anhalt, and Freistaat Thüringen.

4.6.2 Building Size

Now we explore how the energy requirements of buildings differ by the size of buildings, separately still for buildings in the West and East of Germany. The results in Table 4.7 demonstrate that for both regions, larger buildings require less heating energy per heating degree day. Specifically, the largest subgroup of buildings in the West (with more than 20 apartments or households) demand on average 26% less kWh per sqm in response to each heating degree day compared to two-family homes. Interestingly, relative to the West, buildings located in the East consistently demand on average less heat energy per heating degree for each building size category. Taken all together, these results strongly suggest that larger buildings are more energy-efficient.

4.6.3 By Unemployment Rates

Is the distribution of energy-efficiency outcomes regressive? Here we consider effect heterogeneity by the spatial distribution of unemployment rates, an important dimension in socio-economic disparities. Specifically, we seek to answer whether less energy-efficient houses are located in localities marked with higher unemployment rates. In other words, do less economically-secure households live in buildings that do not perform as well in terms of energy-efficiency?

Results in Table 4.8 paint an interesting picture. The majority of the buildings in the East of Germany fall into the top tercile of the unemployment rate distribution, with average unemployment rate of 9.67%. However, we estimate the lowest heat energy requirement per heating degree day for this subgroup of buildings. In contrast, households in the West of Germany living in buildings that are more energy-efficient are located in the zip codes that fall in the lowest tercile of the unemployment rate distribution. The conditional average treatment effects estimated for the West of Germany also highlight potentially larger socio-economic gaps in energy-efficiency outcomes, compared to the localities in the East.

4.6.4 Regional Energy Efficiency

In addition to the East-West divide in Germany, we further expect that differences between states in the West could arise for a number of reasons such as differences in retrofit financing initiatives and take-up, state level mandates such as the 2015 Renewable Heat Act (EWärmeG) in Baden Württermberg that was intended to increase the share of renewable energy in heat supply, or even greener preferences of households.

In this section, we show that states in the East are indeed endowed with more energy-efficient buildings compared to almost all buildings located in the West of Germany. However, there are two large and thus important exceptions - namely, the states of Bavaria and Baden Württermberg.

Figure 4.5 plots the average treatment effects for buildings located in each of the states in West Germany and East defined as one bloc. The differences are ordered in magnitude and associated 95% confidence intervals are shown. We highlight that buildings observed in Baden Württermberg and Bavaria are more energy-efficient compared to the East – demanding less heat energy per square meter on average for each heating degree day.

This is in contrast to the conclusion one would draw from energy performance scores from consumption-based EPCs. Scores on energy-performance certificates are unable to purge the effect of factors such as consumer behaviour, energy prices, and socio-economic factor on the estimated energy performance of buildings. Indeed, households residing in East of Germany are significantly poorer than those in the South (Bavaria and Baden Württermberg). Low energy scores on performance certificates, thus, indicate both that buildings in the East are relatively energy-efficient buildings and the fact that energy consumption is dampened due to low incomes. Indeed, energy performance scores would lead us to conclude that buildings in the East are more energy-efficient than those in the rich states of the South. Using our methodological improvement over the use of energy performance certificates, we are closer to estimating the true potential of buildings – buildings in the South are in fact performing better than those in the East once we account for fixed differences.

4.7 Machine Learning - Causal Forests

The causal forests approach proposed by Wager and Athey (2018) makes it possible to estimate building-specific treatment effects, providing a much more detailed picture of the full extent of heterogeneity in energy-efficiency outcomes.

Causal forests are an extension of the widely used random forest machine learning algorithm described by Breiman (2001) that provide consistent treatment effect estimates conditional on covariates at the individual level. In simplified terms, the method works by splitting the dataset into parts, one of which is used to determine a set of subgroups for estimating heterogeneous effects and the other of which is used to estimate the effects.

Causal forests can fit very flexible nonlinear functions and uncover nonlinear interactions between variables, generating individual treatment effect estimates for each observation. As discussed above, in this case, the treatment effect measures the impact of heating degree days on energy consumed per square meter.

Figure 4.6 is a histogram showing the full distribution of estimated building-specific marginal effects. The average marginal effect is 0.0314, which is similar to the results from the linear regressions reported above. The distribution is slightly negatively skewed; there are more outliers on the efficient (non-responsive to temperature) end of the spectrum than at the other extreme, perhaps because building standards and retrofits have been effective in ensuring a minimum level of energy efficiency.

Examining East and West Germany separately yields an even more interesting picture, as shown in Figure 4.7. The negative skewness is particularly pronounced in the East and much less noticeable in the West, perhaps because of intensive retrofit programs in Eastern states. By further breaking down the distributions by fuel type in Figure 4.12, we can see that an important driver of the greater average efficiency in East Germany is greater efficiency of its district heated buildings - retrofit programs likely explain the significant mass on the left side of the distribution, which is markedly different from the distribution for district heated buildings in West Germany.

Plotting the estimated effects of HDD on energy consumption on a map in Figure 4.13 allows for even more detailed study of geographical patterns - rural buildings appear to be somewhat more efficient than buildings in urban areas on average.

We can also examine how building efficiency varies based on when they were built. As shown in Figure 4.8, newer buildings are more energy efficient. In particular, efficiency seems to start increasing around 1960 and then increases dramatically around 1990. This can also help us understand the East/West distributions we studied below; as shown in 4.9, a much larger share of buildings in East Germany were built after the efficiency improvements of 1990. But more interestingly, significant efficiency improvements had already been made for buildings built before 1975 in the East.

Finally, we can take a more direct look at how estimated effects vary with economic conditions by plotting estimates against unemployment rates. Figure 4.10 shows that zip codes with higher unemployment rates appear to have less efficient buildings on average. However, as shown in Figure 4.11, this effect is much more pronounced in West Germany than in East Germany, again likely due to East German retrofit efforts in the 1990s.

4.8 Discussion

An important limitation of the data we use is that we do not observe detailed information on household or building level socio-economic characteristics that may play an economically significant role in the incentives to improve the energy-efficiency attributes of houses. We resort to using zip-code level information and make the assumption that the location of the building is strongly correlated with the socio-economic background of the tenants - poorer zip codes tend to accommodate poorer households.

We have also considered crucially the non-linear response to temperature shocks in the last decade, in addition to controlling for changes in precipitation and wind conditions. Thus far, we have not examined how effect heterogeneity (by construction year or size of building, for example) varies with heating degree days in different temperature bins. It remains a very interesting extension to the paper, given that the warming climate brings milder winters, leading to the shift of heating degree days from colder to relatively warmer temperature intervals.

Barring these caveats, the main strength of the empirical approach in this paper vis-a-vis ratings on consumption-based energy performance ratings is that by accounting for fixed differences between buildings we are closer to approximating the true energy performance potential of homes. We are able to produce ratings that are more of less consistent with ratings on energy performance certificates with the added benefit that we control for preferences and incomes of users that differ across buildings, for example.

By combining panel data of over 3 million yearly heating bills with daily temperature data at local weather stations, we examine the (historical) realization of energy-efficiency outcomes in the existing building stock. Findings highlight a difference between the distribution of outcomes between the West and the East. In particular, we show that early investments in retrofitting has had a lasting impact in the East of Germany – which is largely missing for the poorer zipcodes in the West of Germany. Results show that the distribution of energy-efficiency is not equitable in the West of Germany, with buildings located in Bavaria and Baden Württemberg attaining the best energy performance standards nationwide. A targeted EE policy should aim to close this energy-efficiency gap, which may be an important dimension of economic inequality.

Finally, our results suggest that the gradual fall in heating degree days due to global warming may be undermining financial incentives for energy-efficiency in the housing sector. We find strong evidence that heat demand declined up until 2014, after which gains in energy-efficiency are not statistically significant. In the absence of interventions such as a carbon price on heating fuel and tax incentives for retrofit programs, climate targets in the housing sector are increasingly out of reach for the German government.

Table 4.1: Buildings by Fuel Type and Number of Apartments

		Building Size by Number of Apts				
Fuel Type	All	2	3 - 6	7 - 12	13 - 20	21 +
Natural Gas H	60%	6.4	28.6	15.1	5.0	4.6
Natural Gas L	1.2%	0.1	0.4	0.4	0.2	0.2
District Heating	10%	0.2	1.8	2.4	1.6	4.1
Oil	29%	6.4	16.3	4.1	1.1	1.1
Total	100%	13%	47%	22%	8%	10%

Notes: This table show the distribution of the 3,030,063 sample of heating bills by fuel type and building size. The sample covers buildings that were billed starting from January 2008 to June 2018.

Table 4.2: Regional Shares

State	Observations	Percent	# of Zip Codes	Buildings
Schleswig-Holstein	56,792	1.9	361	7,245
Hamburg	56,900	1.9	97	8,101
Niedersachsen	291,197	9.6	782	36,623
Bremen	27,147	0.9	34	3,314
Nordrhein-Westfalen	769,198	25.4	864	100,811
Hessen	303,301	10.0	535	38,287
Rheinland-Pfalz	127,026	4.2	627	15,580
Baden-Württemberg	379,418	12.5	1146	46,072
Bayern	427,125	14.1	1864	52,366
Saarland	22,590	0.8	68	2,799
Berlin	117,986	3.9	189	15,538
Brandenburg	63,946	2.1	210	7,913
Mecklenburg-Vorpommern	61,771	2.0	186	7,932
Sachsen	194,499	6.4	388	24,230
Sachsen-Anhalt	80,564	2.7	207	10,712
Thüringen	50,603	1.7	211	6,404
Total	3,030,063	100	7,769	384,223

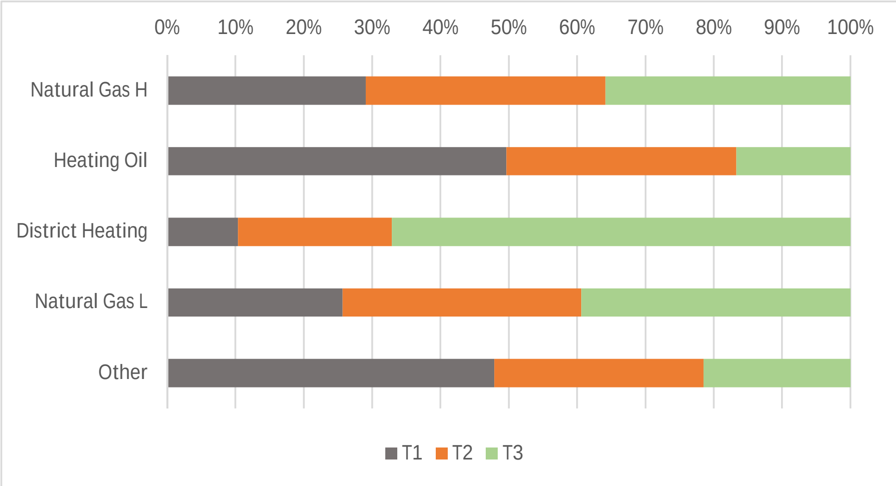
Notes: This table shows the number of heating bills observed in the full sample for each of the 16 states.

Table 4.3: Summary Statistics

	Energy Use, Price, Building Size			Heating Degree Days		Energy Performance Certificates		
Bill Start	kWh/m^2	Cents/kWh	# of Apts	Local	Δ from "Typical"	Vintage	WSVO 1995	Heat System
2008	128.5 (116.7)	6.8 (7.6)	9.1 (15.8)	2283.8	-110.3	1966.6 (1949.2)	0.36 (0.52)	1996.5 (1996.7)
2009	128.6 (119.2)	6.4 (7.2)	9.6 (17.1)	2362.4	-31.8	1966.4 (1949.9)	0.37 (0.51)	1996.5 (1996.7)
2010	128.6 (132.4)	6.0 (6.7)	9.8 (17.2)	2652.7	258.5	1966.9 (1950.3)	0.37 (0.52)	1996.6 (1996.8)
2011	118.3 (112.6)	6.7 (7.7)	9.6 (17.1)	2137.6	-256.6	1966.5 (1950.1)	0.37 (0.52)	1996.6 (1996.9)
2012	125.0 (117.2)	7.3 (8.2)	9.7 (17.3)	2405.1	10.9	1966.6 (1950.3)	0.37 (0.52)	1996.7 (1996.8)
2013	122.8 (119.0)	7.5 (8.4)	9.9 (17.4)	2336.9	-57.2	1966.5 (1950.4)	0.38 (0.52)	1996.8 (1996.9)
2014	106.9 (99.8)	7.4 (8.6)	10.1 (17.3)	1947.0	-447.2	1966.2 (1950.4)	0.38 (0.52)	1996.8 (1997.0)
2015	112.5 (105.1)	6.6 (7.3)	10.0 (17.2)	2071.1	-323.0	1966.5 (1950.6)	0.38 (0.52)	1996.9 (1997.0)
2016	118.8 (111.2)	5.9 (6.7)	10.2 (17.7)	2261.0	-133.2	1966.9 (1950.9)	0.38 (0.51)	1996.9 (1997.0)
2017	117.6 (109.9)	5.6 (6.3)	10.4 (18.1)	2159.5	-234.6	1967.6 (1951.5)	0.38 (0.52)	1997.1 (1997.2)
2018	111.4 (103.2)	5.6 (6.4)	11.0 (18.6)	2066.0	-328.2	1969.3 (1953.3)	0.39 (0.53)	1997.2 (1997.2)
All Years	120.7 (113.3)	6.6 (7.4)	9.9 (17.4)	2248.2	-146.0	1966.8 (1950.6)	0.37 (0.52)	1996.8 (1996.9)

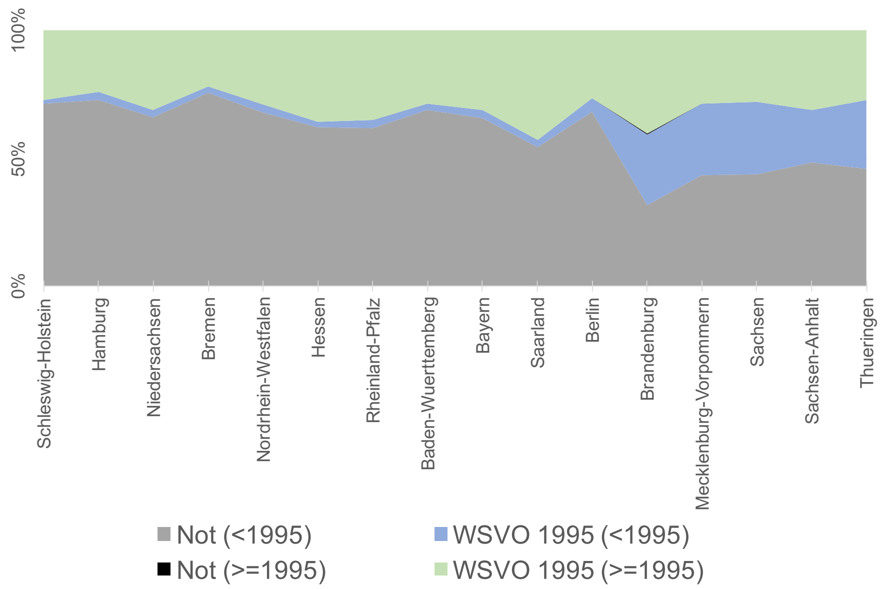
Notes: The table reports statistics for the full sample. All values are averages, calculated for each year in which the 12-month billing period starts for the observed building. The values in parentheses are average for the East of Germany located in Berlin, Brandenburg, Mecklenburg-Vorpommern, Sachsen, Sachsen-Anhalt, and Thüringen. The second and third columns report on building-level energy use and heating costs for the full sample of buildings described in section 3.1. Energy use is measured as the annual heat energy consumption per square meter of heated living space. Price of heating fuel is given in euro cents per kWh. Building size is given by the column indicating the number of apartments. The "Local" column reports the average annual sum of heating degree days (with daily mean temperature below 15 degree Celsius) recorded at the nearest weather station from 20080101 to 20181231, while the second column under "Typical" reports the difference in the annual sum of heating degree days recorded at the local station compared to that recorded from 1995 to 2012 at Potsdam. The last three columns report data from energy performance certificates. The WSVO 1995 column reports the share of buildings reporting energy performance certificates from 2014 to 2019 that meet thermal insulation standards effective in 1995.

Figure 4.1: Fuel Type by Terciles of the Unemployment Rate



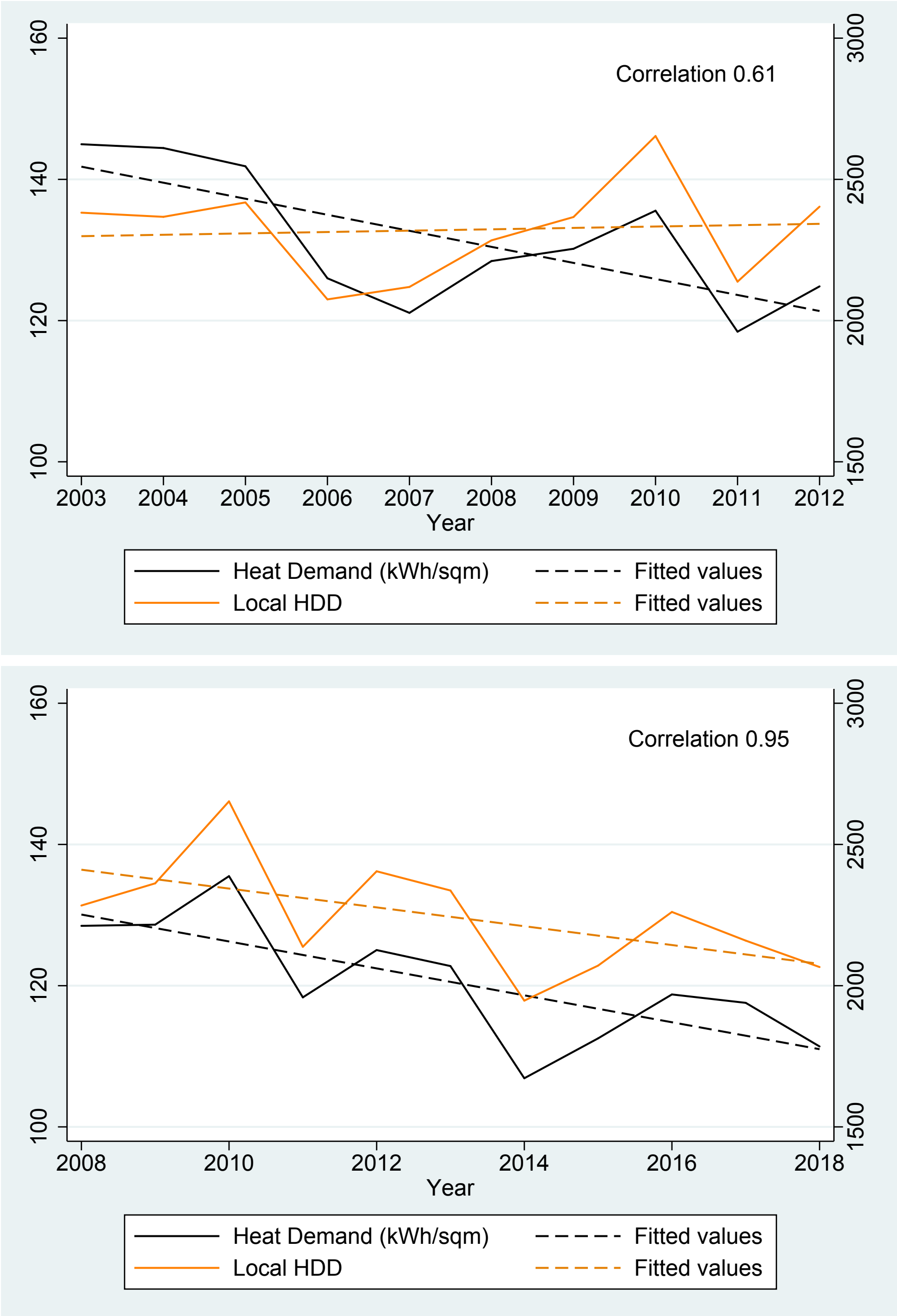
Notes: This figure shows the distribution of main fuel types used by buildings in the sample by terciles of the unemployment rate, defined using data from RWI-GEO-GRID.

Figure 4.2: WSVO 1995 Standards



Notes: The graph summarizes the share of buildings that are certified to meet the thermal insulation standards of 1995 (WSVO 1995) by year of construction (built before or after 1995). A building is defined to meet the 1995 insulation standards, if it is certified that all five building components (the roof, top ceiling, outer wall, windows, and basement) meet the 1995 minimum energy standards. The grey colored area indicates the share of buildings by state that were built before 1995 and do not meet WSVO 1995 insulation standards. Here we clearly show that buildings, built before 1995, in the East German states were much more likely to be renovated to meet the WSVO 1995 standard. We also show that there almost all buildings built 1995 onwards did pass certification for WSVO 1995.

Figure 4.3: Decline in Heat Demand (lhs) and Heating Degree Days (rhs)



Notes: The graph plots simple averages of annual heat energy consumption for the full sample against the starting year of each billing or heating period (rolling 12-months). The left y-axis measures the annual kWh per square meter of heated living space per building, while the right y-axis measures the number of heating degree days – heating degrees recorded on days with temperatures below 15 Celsius, recorded at the nearest weather station to each building's zip code. Source: authors' calculations using data described in Section 3.

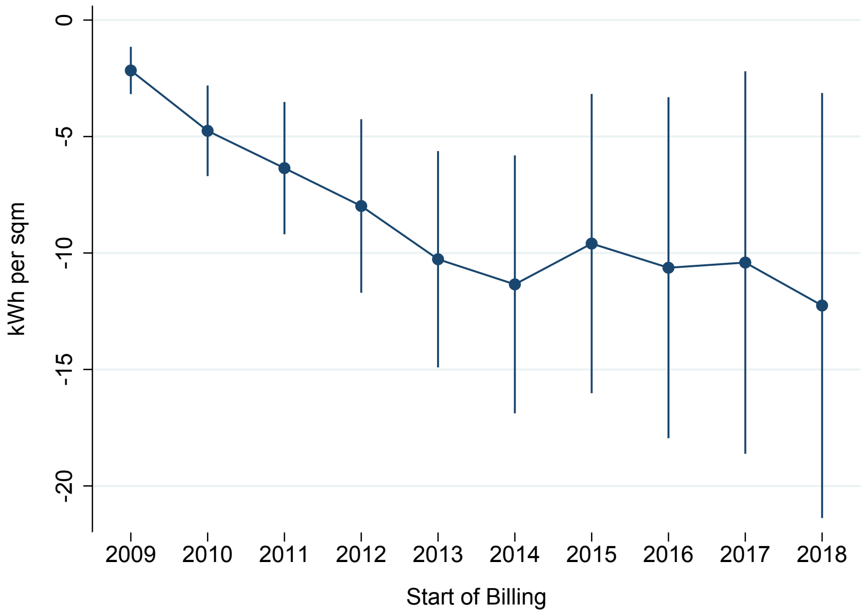
Table 4.4: Response of Heat Energy Demand to Temperature

Full Sample of Buildings

	Dependent variable: kWh/m^2			
	(1)	(2)	(3)	(4)
Local HDD	0.0312***	0.0306***	0.0306***	0.0303***
	(0.0002)	(0.0002)	(0.0003)	(0.0002)
Price (Euros/kWh)			-3.262***	
			(0.476)	
Unemployment (%)			-0.0902	
			(0.0661)	
Purchasing Power per HH			0.148****	
			(0.0217)	
Building Size			-0.230***	
			(0.0598)	
Apartment Size			-0.0423***	
			(0.00687)	
Zip Code Density			-0.0176***	
			(0.00304)	
Building FE	Yes	Yes	Yes	Yes
Fuel Type FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bill Start Year FE	Yes	Yes	Yes	Yes
Fuel Type x Year FE		Yes	Yes	Yes
Zip Code x Year FE				Yes
N	3,030,063	3,030,063	2,252,758	3,023,892
Adj R^2	0.776	0.776	0.790	0.780

*Notes:*The full sample covers all buildings using natural gas (high or low calorific), district heating, and oil. The dependent variable is kilowatt hours consumed per square meter of heated living space. Standards errors are clustered at the zip code level for all specifications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 4.4: Decline in Heat Demand Relative to 2008



Notes: The graph illustrates how annual heat demand has changed relative to the base year of 2008. These are coefficient estimates drawn from a regression of heat demand on HDD, disaggregated by 5 temperature bins in the interval $(-\infty, 15)$, controlling for heating costs, along with fixed effects for building, fuel type, (majority) year of billing and fuel type by year of billing. 95% confidence intervals provided. Standards errors were clustered at the zip-code level.

Table 4.5: Standards for New Construction

Year	Regulation	Max. per annum
Pre-1978	No regulation	
1978	Heat insulation (WSchV)	250 kWh/m^2
1984	Amendment of WSchV	220 kWh/m^2
1995	Amendment of WSchV	150 kWh/m^2
2002	Energy saving (EnEV)	100 kWh/m^2
2009	Amendment of EnEV	60 kWh/m^2
2016	Amendment of EnEV	45 kWh/m^2
2021	Amendment of EnEV	0 kWh/m^2

Notes: The first column indicates the year in which the regulation became effective. Sources: Ray and Sunikka-Blank (2013), El-Shagi et al. (2017)

Table 4.6: Temperature Response By Year of Construction

	West Germany Response of kWh/m^2					
	(1)	(2)	(3)	(4)	(5)	(6)
	Pre-1978	1978-1983	1984-1994	1995-2001	2002-2008	2009+
Local HDD	0.0367***	0.0309***	0.0248***	0.0169***	0.0109***	0.0176**
	(0.0004)	(0.0006)	(0.0004)	(0.0004)	(0.0005)	(0.0018)
$N = 1,045,616$						
Adj R^2 = 0.7706						
Share	0.50	0.10	0.22	0.14	0.04	0.001
Avg. Vintage	1952	1981	1990	1997	2004	2010

	East Germany Response of kWh/m^2					
	(1)	(2)	(3)	(4)	(5)	(6)
	Pre-1978	1978-1983	1984-1994	1995-2001	2002-2008	2009+
Local HDD	0.0300***	0.0237***	0.0238***	0.0207***	0.0171***	0.0303***
	(0.0001)	(0.0013)	(0.0011)	(0.0001)	(0.0016)	(0.0077)
$N = 317,401$						
Adj R^2 = 0.8301						
Share	0.66	0.04	0.10	0.18	0.01	0.001
Avg. Vintage	1929	1980	1990	1997	2004	2010

Notes: Table presents coefficients on the interactions between Local HDD and Building Codes. The specification includes fixed effects for building, fuel type, (majority) year of billing, the starting year of each billing period, and fuel type by year. The sample covers all buildings using natural gas (high or low calorific), district heating, and oil. The dependent variable is kilowatt hours consumed per square meter of heated living space. Standards errors are clustered at the zip code level for all specifications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4.7: Temperature Response By Size of Building (# of Apartments)

			West Germany Response of kWh/m^2		
	(1)	(2)	(3)	(4)	(5)
	2 HH	3 - 6 HH	7 - 12 HH	13 - 20 HH	21+ HH
Local HDD	0.0354***	0.0314***	0.0285***	0.0271***	0.0261***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
$N = 2,460,694$					
Adj R^2 = 0.9667					
Share	0.15	0.51	0.21	0.07	0.07
Avg. Building Size	2 Apts	4.22	8.99	15.98	42.97

			East Germany Response of kWh/m^2		
	(1)	(2)	(3)	(4)	(5)
	2 HH	3 - 6 HH	7 - 12 HH	13 - 20 HH	21+ HH
Local HDD	0.0325***	0.0287***	0.0267***	0.0256***	0.0243***
	(0.0011)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
$N = 569,369$					
Adj R^2 = 0.8184					
Share	0.04	0.31	0.27	0.13	0.25
Avg. Building Size	2 Apts	4.64	9.23	16.23	45.57

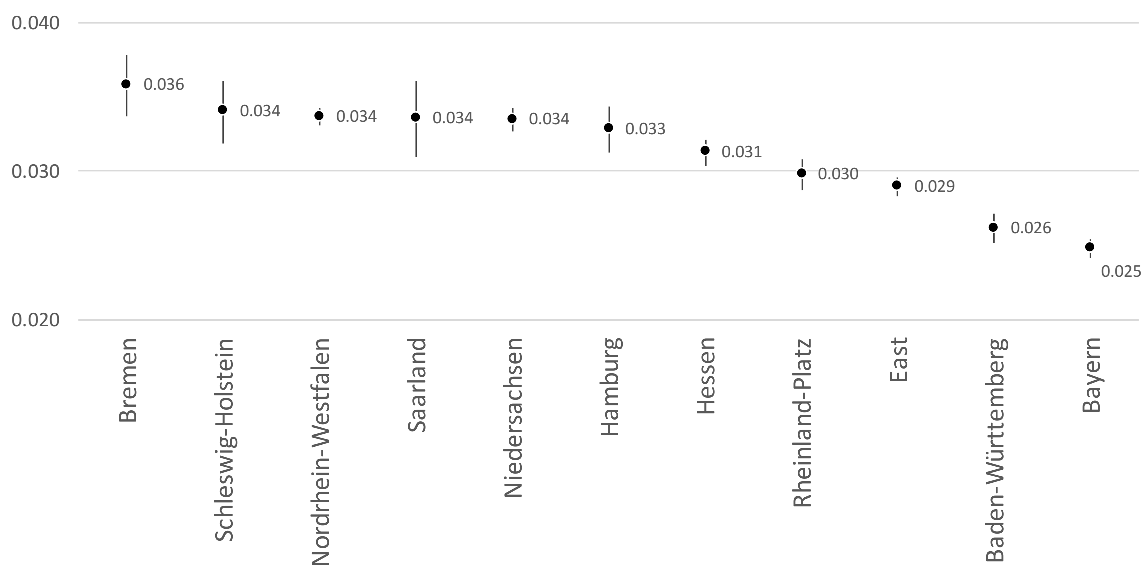
Notes: Table presents coefficients on the interactions between Local HDD and Building Size. The specification includes fixed effects for building, fuel type, (majority) year of billing, the starting year of each billing period, and fuel type by year. The sample covers all buildings using natural gas (high or low calorific), district heating, and oil. The dependent variable is kilowatt hours consumed per square meter of heated living space. Standards errors are clustered at the zip code level for all specifications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4.8: Temperature Response By Terciles of the Unemployment Rate

	West Germany Response of kWh/m^2		
	(1)	(2)	(3)
	T1	T2	T3
Local HDD	0.0279***	0.0306***	0.0332***
	(0.0004)	(0.0003)	(0.0003)
$N = 2,107,369$			
Adj R^2 = 0.7737			
Share	0.25	0.39	0.36
Avg. Unemployment %	2.26	4.22	8.65
	East Germany Response of kWh/m^2		
	T1	T2	T3
Local HDD	0.0309***	0.0275***	0.0270***
	(0.0020)	(0.0001)	(0.0006)
$N = 569,369$			
Adj R^2 = 0.8184			
Share	0.01	0.09	0.90
Avg. Unemployment %	2.14	4.46	9.67

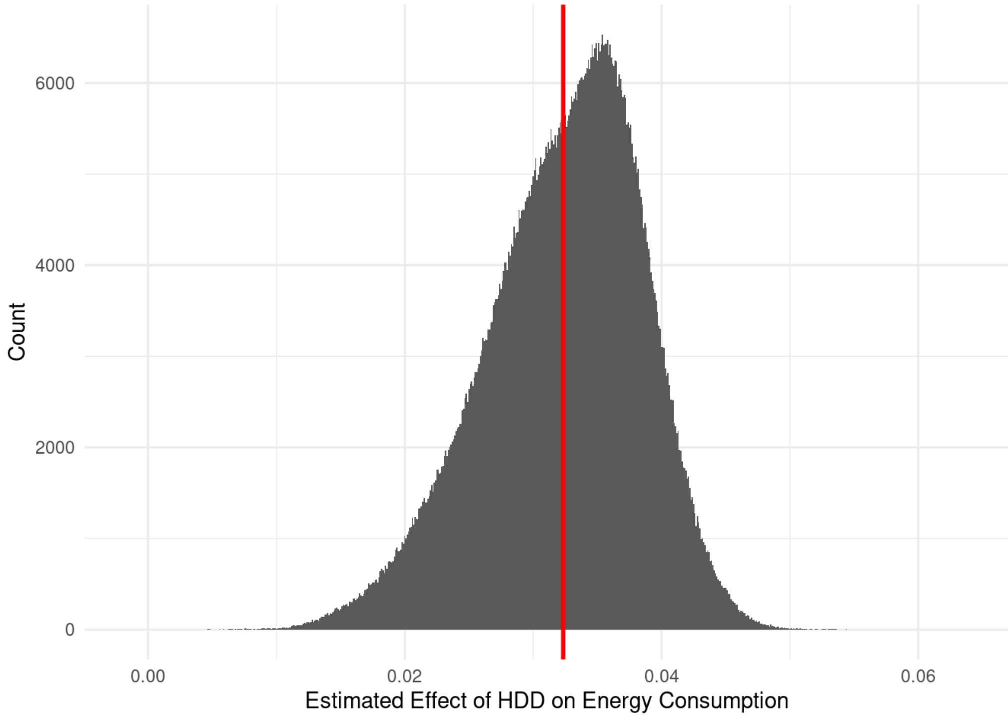
Notes: Table presents coefficients on the interactions between Local HDD and indicators for terciles of the unemployment rate distribution. The specification includes fixed effects for building, fuel type, (majority) year of billing, the starting year of each billing period, and fuel type by year. The sample was limited to years 2009 to 2017, for which the unemployment rates were available. The last row reports the average unemployment rate for each tercile. The sample covers all buildings using natural gas (high or low calorific), district heating, and oil. The dependent variable is kilowatt hours consumed per square meter of heated living space. Standards errors are clustered at the zip code level for all specifications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 4.5: Energy Efficiency by States



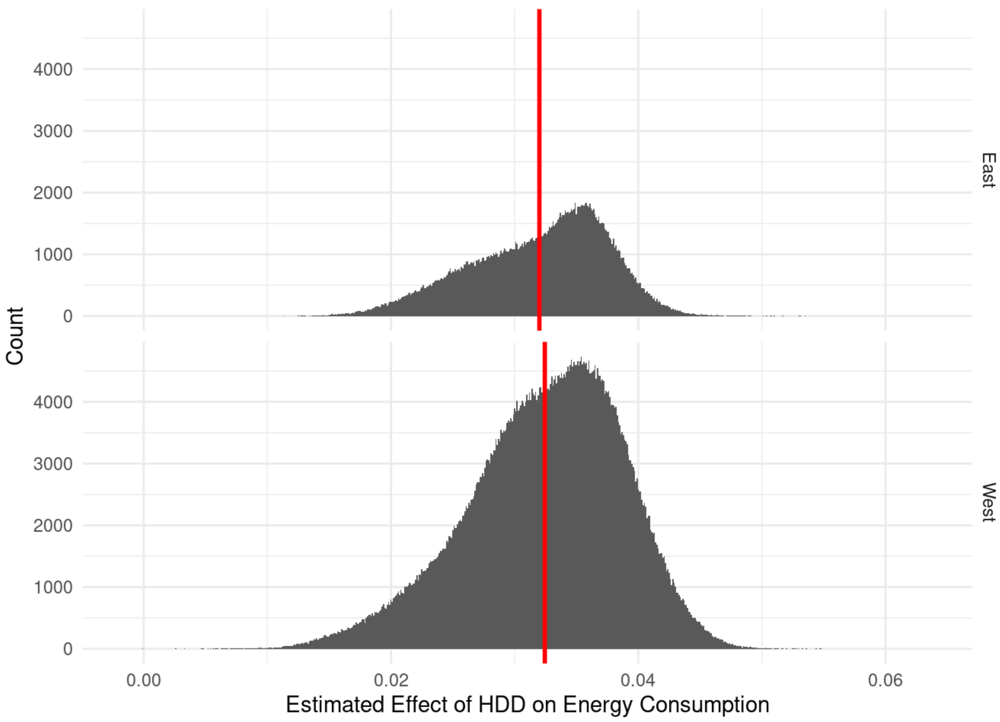
Notes: The graph presents the differences in the average treatment effect for each state in West Germany and states in the East pooled in one group. Corresponding 95 % confidence intervals are shown. The coefficients come from a regression that include fixed effects for building, fuel type, (majority) year of billing, the starting year of each billing period, and fuel type by year. The sample covers all buildings using natural gas (high or low calorific), district heating, and oil. Standards errors were clustered at the zip code level.

Figure 4.6: Distribution of Marginal Effects



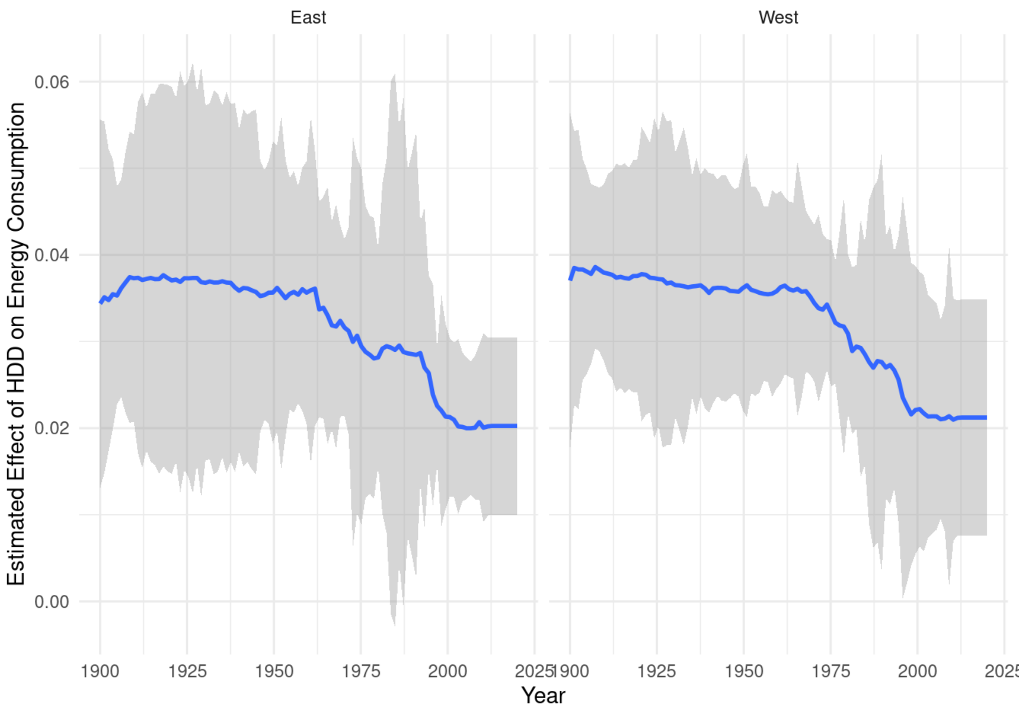
Notes: The graph is a histogram showing the full distribution of building-specific marginal effects, generated using causal forests. In this case, the marginal effect measures the impact of heating degree days on energy consumed per square meter.

Figure 4.7: Distribution by East and West Germany



Notes: The graph shows the full distribution of building-specific marginal effects for East and West Germany generated using causal forests.

Figure 4.8: Marginal Effects by Construction Year



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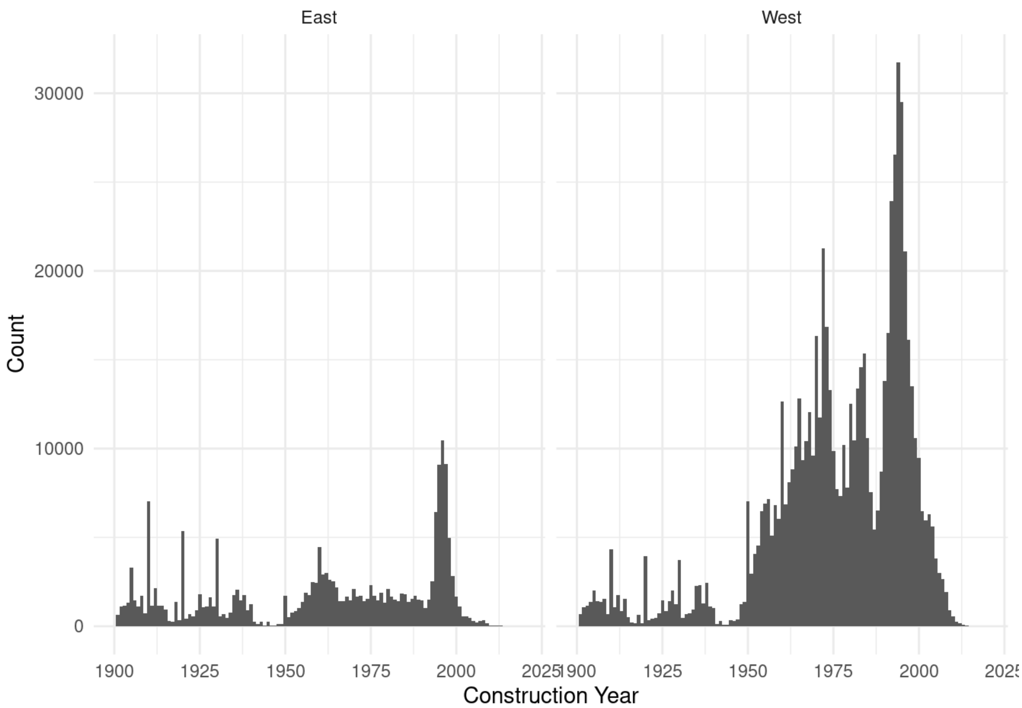
Notes: The graph shows how the marginal effects generated using causal forests vary over construction year, holding all other variables constant at the sample mean.

Figure 4.9: Distribution of Buildings by Construction Year



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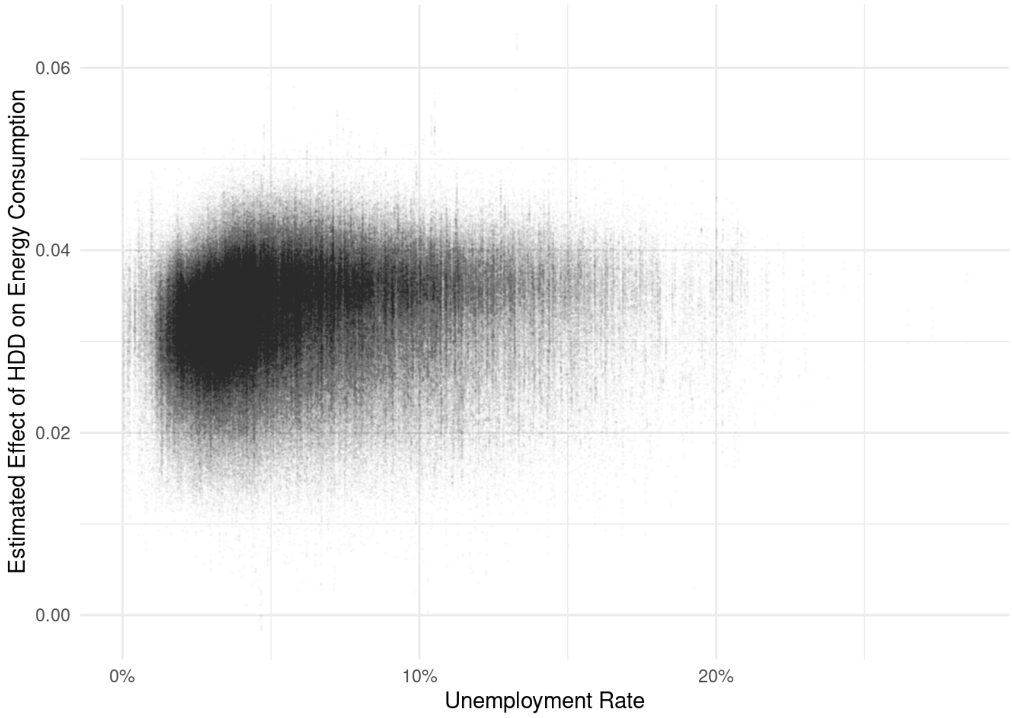
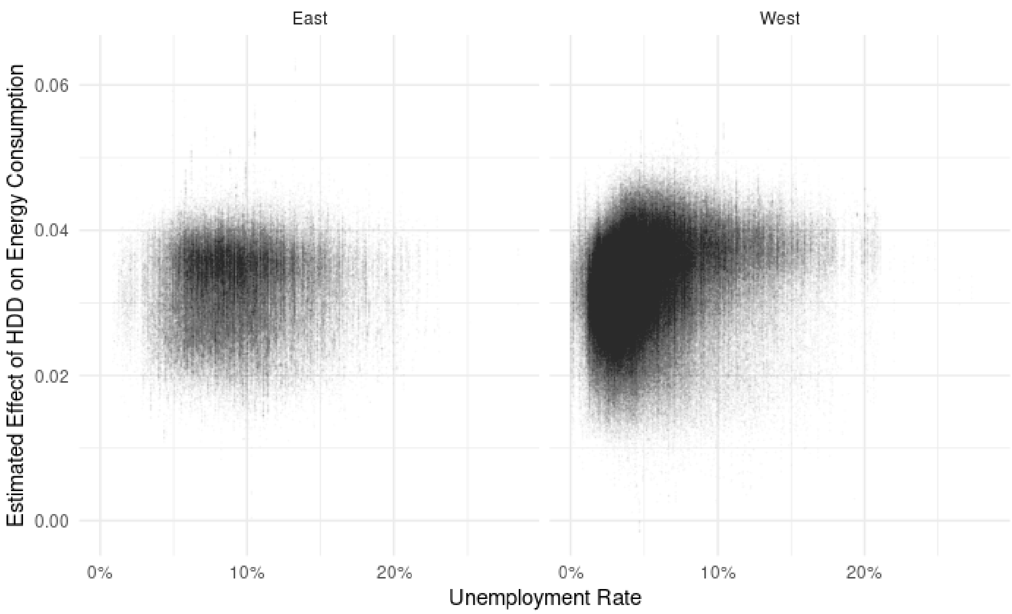
Notes: The graph plots the frequency of buildings observed by construction year, separately for East and West Germany.

Figure 4.10: Marginal Effects By Unemployment Rates



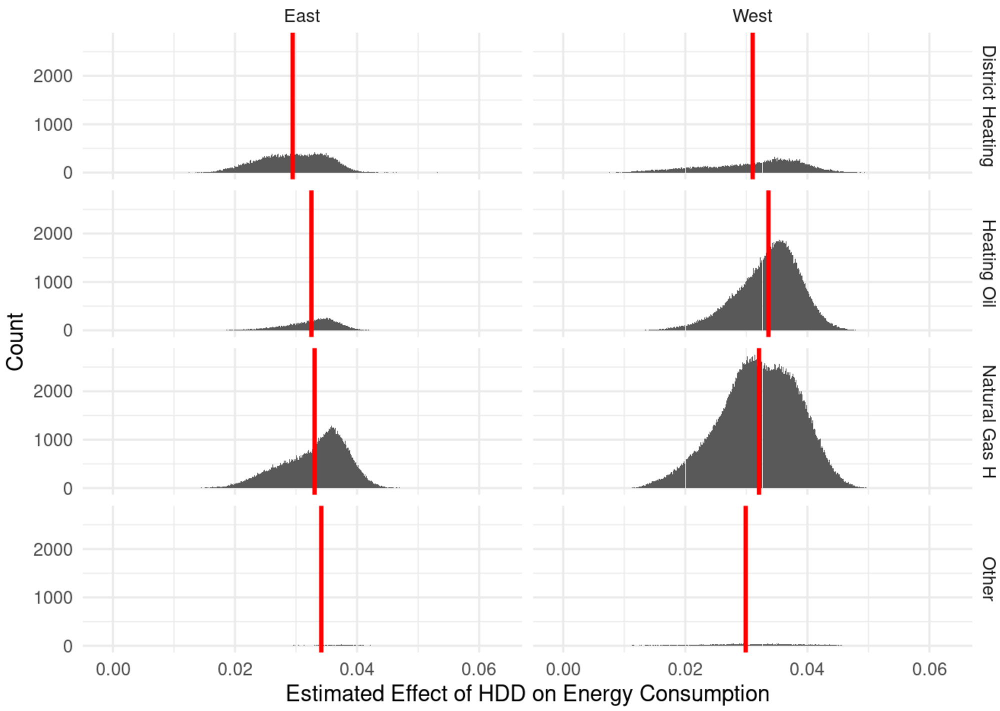
Notes: The graph shows how ML-based building-specific marginal effects vary with the corresponding zipcode's average unemployment rate.

Figure 4.11: Marginal Effects By Unemployment Rates: East & West



Notes: The graph shows how ML-based building-specific marginal effects vary with the corresponding zipcode's average unemployment rate, separately for East and West Germany.

Figure 4.12: Marginal Effects by Fuel Type



Notes: The graph shows the distribution of ML-based building-specific marginal effects by main fuel type in East and West Germany.

4.9 Appendix

Table 4.9: Shares of Fuel Type by Planning Regions (ROR) - Tercile 1

T1 of the Unemployment Rate

		Microcensus 2010			Building Sample		
State	ROR No.	District Heat	Oil	Natural Gas	District Heat	Oil	Natural Gas
Bayern	907	0.08	0.44	0.48	0.05	0.54	0.41
Bayern	908	0.00	0.59	0.41	0.02	0.49	0.48
Bayern	901	0.05	0.60	0.35	0.03	0.53	0.44
Bayern	915	0.00	0.63	0.37	0.02	0.52	0.46
Bayern	904	0.05	0.58	0.37	0.04	0.52	0.44
Bayern	917	0.00	0.63	0.37	0.01	0.59	0.40
Bayern	910	0.23	0.32	0.45	0.12	0.37	0.52
Average		0.06	0.54	0.40	0.04	0.51	0.45

Notes: The table compares the shares of main fuel types by planning regions from the official Microcensus statistics from 2010 and the data sample used in the paper. A planning region falls into the tercile (T1) with the lowest unemployment rates, if more than 75 % of the zipcodes fall into T1. The data for the unemployment rate come from RWI and microm (2020) and Microcensus data from Destatis (2012).

Table 4.10: Shares of Fuel Type by Planning Regions (ROR) - Tercile 3

T3 of the Unemployment Rate

		Microcensus 2010			Building Sample		
State	ROR No.	District Heat	Oil	Natural Gas	District Heat	Oil	Natural Gas
Mecklenburg-Vorpommern	1301	0.58	0.15	0.27	0.15	0.32	0.53
Mecklenburg-Vorpommern	1303	0.58	0.11	0.30	0.34	0.08	0.58
Sachsen-Anhalt	1502	0.41	0.18	0.41	0.23	0.11	0.67
Sachsen-Anhalt	1503	0.43	0.16	0.40	0.27	0.13	0.60
Sachsen-Anhalt	1501	0.40	0.15	0.44	0.30	0.04	0.65
Sachsen	1404	0.41	0.09	0.50	0.20	0.07	0.73
Mecklenburg-Vorpommern	1302	0.64	0.04	0.32	0.43	0.03	0.54
Brandenburg	1205	0.54	0.10	0.35	0.33	0.16	0.51
Mecklenburg-Vorpommern	1304	0.46	0.09	0.45	0.31	0.06	0.63
Sachsen	1401	0.45	0.08	0.47	0.40	0.05	0.55
Brandenburg	1202	0.51	0.13	0.36	0.23	0.12	0.66
Sachsen-Anhalt	1504	0.37	0.10	0.54	0.17	0.07	0.76
Brandenburg	1203	0.47	0.04	0.49	0.42	0.03	0.55
Nordrhein-Westfalen	509	0.23	0.13	0.65	0.21	0.13	0.65
Sachsen	1402	0.34	0.18	0.48	0.25	0.10	0.65
Thueringen	1603	0.37	0.17	0.46	0.18	0.09	0.73
Berlin	1101	0.44	0.21	0.35	0.28	0.24	0.48
Bremen	401	0.27	0.18	0.55	0.04	0.27	0.68
Sachsen	1403	0.29	0.14	0.57	0.16	0.09	0.76
Niedersachsen	312	0.05	0.02	0.93	0.04	0.05	0.91
Thueringen	1601	0.38	0.11	0.52	0.20	0.05	0.75
Nordrhein-Westfalen	506	0.10	0.15	0.75	0.10	0.18	0.72
Schleswig-Holstein	103	0.20	0.21	0.59	0.05	0.25	0.70
Thueringen	1602	0.34	0.15	0.51	0.13	0.06	0.81
Nordrhein-Westfalen	507	0.27	0.15	0.57	0.18	0.16	0.66
Brandenburg	1204	0.42	0.15	0.44	0.35	0.10	0.56
Average		0.38	0.13	0.49	0.23	0.12	0.65

Notes: The table compares the shares of main fuel types by planning regions from the official Microcensus statistics from 2010 and the data sample used in the paper. A planning region falls into the tercile (T3) with the highest unemployment rates, if more than 75 % of the zipcodes fall into T3. The data for the unemployment rate come from RWI and microm (2020) and Microcensus data from Destatis (2012).

Figure 4.13: Geographical Distribution of Buildings & Treatment Effects

Notes: The graph maps the location of each building used in the main analysis. Each dot represents a building in the sample.

Table 4.11: Non-Linearities in Temperature Response

	Dependent variable: kWh/m^2		
	(1)	(2)	(3)
	Full	"Altbau"	Not WSVO1995
HDD if (°C < -5)	0.0255***	0.0280***	0.0279***
	(0.0003)	(0.0005)	(0.0006)
HDD if (-5 ≤ °C < 0)	0.0307***	0.0330***	0.0322***
	(0.0003)	(0.0004)	(0.0005)
HDD if (0 ≤ °C < 5)	0.0266***	0.0284***	0.0282***
	(0.0004)	(0.0005)	(0.0008)
HDD if (5 ≤ °C < 10)	0.0232***	0.0253***	0.0255***
	(0.0005)	(0.0007)	(0.0011)
HDD if (10 ≤ °C < 15)	0.0210***	0.0259***	0.0275***
	(0.0010)	(0.0014)	(0.0021)
Interaction Terms			
		X "Neubau"	X WSVO1995
HDD if (°C < -5)		-0.0125***	-0.00681***
		(0.0005)	(0.0009)
HDD if (-5 ≤ °C < 0)		-0.0149***	-0.0105***
		(0.0004)	(0.0005)
HDD if (0 ≤ °C < 5)		-0.0123***	-0.00887***
		(0.0005)	(0.0008)
HDD if (5 ≤ °C < 10)		-0.0139***	-0.0102***
		0.0007)	(0.0010)
HDD if (10 ≤ °C < 15)		-0.0182***	-0.0123***
		(0.0014)	(0.0024)
N	3,030,063	1,363,017	439,126
Adj R^2	0.777	0.785	0.800
Zip Codes	7,769	6,860	5,340

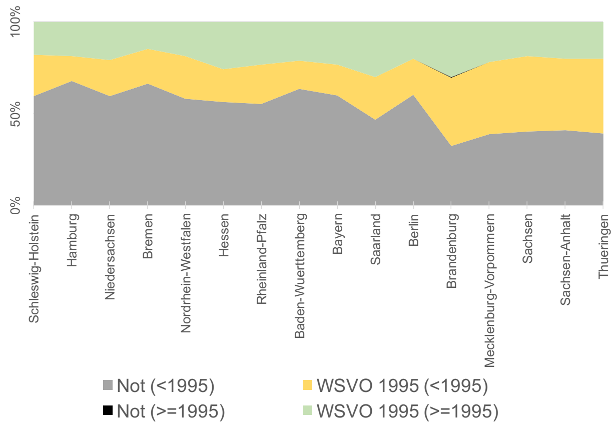
Notes: The full sample covers all buildings using natural gas (high or low calorific), district heating, and oil. The dependent variable is kilowatt hours consumed per square meter of heated living space. "Altbau" equals 1 if the building was constructed before 1995. "Neubau" are buildings built starting 1995. WSVO 1995 is a composite measure indicating whether the roof, loft ceiling, windows, outer wall, and basement ceiling met thermal insulation standards under the 1995 building codes. This information was only available from energy performance certificates issued from 2014 to 2019. Standards errors are clustered at the zip code level for all specifications. All regressions include fixed effects for building, fuel type, (majority) year of billing, the starting year of each billing period, and fuel type by year. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4.12: Accounting for Other Weather Variation

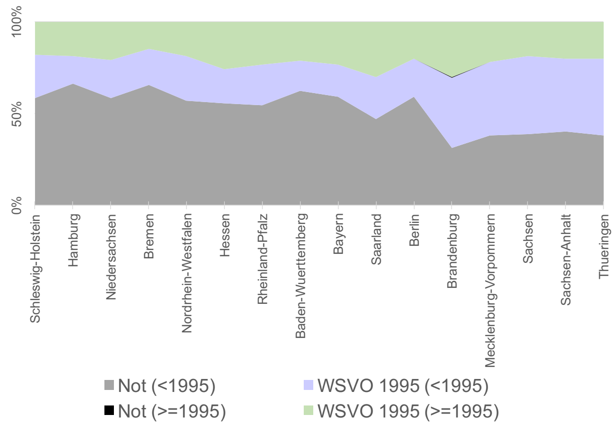
	Dependent variable: kWh/m^2			
	(1)	(2)	(3)	(4)
HDD	0.0306***		0.0306***	
	(0.0002)		(0.0002)	
HDD if (°C < -5)		0.0255***		0.0253***
		(0.0003)		(0.0003)
HDD if (-5 $\leq$ °C < 0)		0.0307***		0.0305***
		(0.0003)		(0.0003)
HDD if (0 $\leq$ °C < 5)		0.0266***		0.0262***
		(0.0004)		(0.0004)
HDD if (5 $\leq$ °C < 10)		0.0232***		0.0227***
		(0.0005)		(0.0005)
HDD if (10 $\leq$ °C < 15)		0.0210***		0.0197***
		(0.0010)		(0.0010)
Precipitation (mm)			-0.0565**	-0.0547**
			(0.0212)	(0.0200)
Humidity (%)			0.691***	0.907***
			(0.112)	(0.105)
N	3,030,063	3,030,063	3,030,063	3,030,063
Adj R^2	0.776	0.777	0.776	0.777

Notes: The full sample covers all buildings using natural gas (high or low calorific), district heating, and oil. The coefficient on the HDD should be interpreted as the increase in kWh per square meter living space for each 1°C increase in the annual sum of heating degree days, with mean temperatures below 15°C. Similarly in the sixth row, the coefficient should be interpreted as the increase in kWh per square meter for each 1°C increase in the annual sum of heating degree days, with mean temperatures inside the interval (10 $\geq$ °C < 15). Precipitation is the average of total precipitation height (mm) on days with mean temperatures below 15°C. Relative humidity is the average of the mean relative humidity (%) on days with mean temperatures below 15°C. Standards errors are clustered at the zip code level for all specifications. All regressions include fixed effects for building, fuel type, (majority) year of billing, the starting year of each billing period, and fuel type by year. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

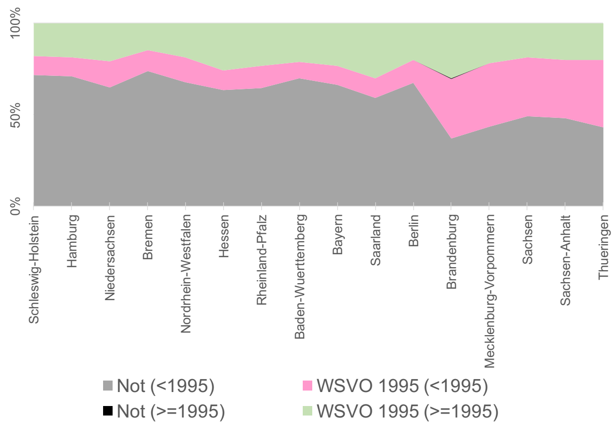
Figure 4.14: WSVO 1995 By Component



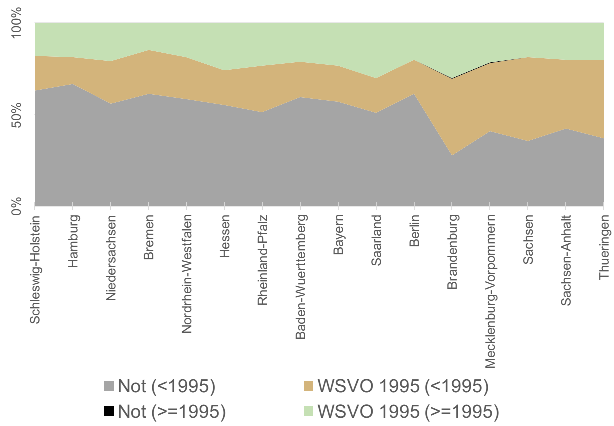
(a) Roof



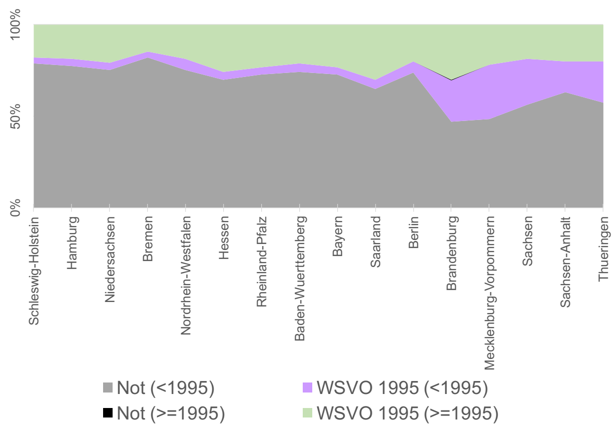
(b) Loft Ceiling



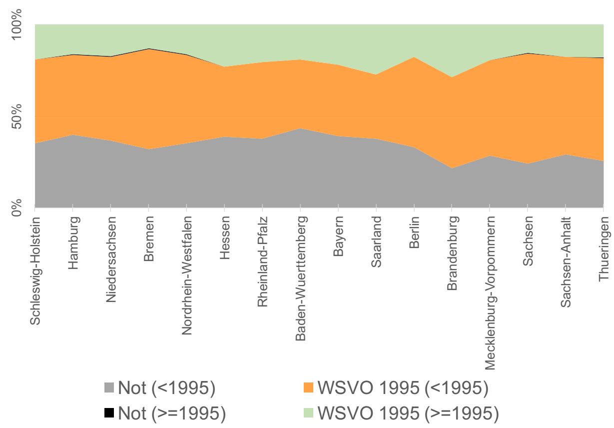
(c) Outer Wall



(d) Windows



(e) Basement



(f) Heating System

Notes: The graphs summarize the share of buildings that are certified to meet the minimum thermal insulation standards of 1995 for all six building components (the roof, loft or top ceiling, outer wall, windows, basement ceiling, and the heating system).

Bibliography

AGEB (2018). Anwendungsbilanzen für die Endenergiesektoren in Deutschland in den Jahren 2013 bis 2017. Report, AG Energiebilanzen e.V. (available online, in German).

Allcott, H. and Greenstone, M. (2017). Measuring the welfare effects of residential energy efficiency programs. *NBER Working Paper*, 23386.

Becker, R. and Henderson, V. (2000). Effects of air quality regulations on polluting industries. *Journal of Political Economy*, 108(2):379–421.

Bento, A. M. (2013). Equity impacts of environmental policy. *Annu. Rev. Resour. Econ.*, 5(1):181–196.

BMWi (2019). Zahlen und Fakten, Energiedaten. Report, Federal Ministry for Economic Affairs and Energy. (available online, in German).

Breidenbach, P. and Eilers, L. (2018). RWI-GEO-GRID: Socio-economic data on grid level. *Jahrbücher für Nationalökonomie und Statistik*, 238(6):609–616.

Breiman, L. (2001). Random forests. *Machine learning*, 45(1):5–32.

Bruegge, C., Deryugina, T., and Myers, E. (2019). The distributional effects of building energy codes. *Journal of the Association of Environmental and Resource Economists*, 6(2):95–127.

Bushnell, J. B. and Wolfram, C. D. (2012). Enforcement of vintage-differentiated regulations: The case of new source review. *Journal of Environmental Economics and Management*, 64:137–152.

Chay, K. Y. and Greenstone, M. (2003). Air Quality, Infant Mortality, and the Clean Air Act of 1970. *NBER Working Paper*, 10053.

Chetty, R., Looney, A., and Kroft, K. (2009). Salience and taxation: Theory and evidence. *American Economic Review*, 99(4):1145–1177.

Christensen, P., Francisco, P., Myers, E., and Souza, M. (2020). Decomposing the wedge between projected and realized returns in energy efficiency programs. *E2e Working Paper*, 046.

DellaVigna, S. (2009). Psychology and economics: Evidence from the field. *Journal of Economic Literature*, 47(2):315–372.

DellaVigna, S. and Pollet, J. (2009). Investor inattention and friday earnings announcements. *The Journal of Finance*, 64(2):709–749.

Destatis (2012). Bauen und Wohnen. Mikrozensus - Zusatzerhebung 2010. Report, Statistisches Bundesamt, Wiesbaden. (available online, in German).

Destatis (2016). Bauen und Wohnen. Mikrozensus - Zusatzerhebung 2014. Report, Statistisches Bundesamt, Wiesbaden. (available online, in German).

EEA (2016). Reported information under Directive 2001/80/EC on large combustion plants. European Environmental Agency. Database Version 3.1. Accessed 20.12.2017.

EEA (2017). Air quality in Europe â 2017 report. Report No. 13/2017.

EEA (2018a). Reported data on large combustion plants covered by the Industrial Emissions Directive (2010/75/EU). European Environmental Agency. Database Version 4.0. Accessed 14.05.2018.

EEA (2018b). Reported data on large combustion plants covered by the Industrial Emissions Directive (2010/75/EU). European Environmental Agency. Database Version 4.2. Accessed 07.01.2019.

El-Shagi, M., Michelsen, C., and Rosenschon, S. (2017). Empirics on the long-run effects of building energy codes in the housing market. *Land Economics*, 93(4):585–607.

Finkelstein, A. (2009). E-ztax: Tax salience and tax rates. *Quarterly Journal of Economics*, 124(3):969–1010.

Fowlie, M., Greenstone, M., and Wolfram, C. (2018). Do energy efficiency investments deliver? evidence from the weatherization assistance program. *The Quarterly Journal of Economics*, 133(3):1597–1644.

Gerarden, T. R., Newell, R. G., and Stavins, R. N. (2017). Assessing the energy-efficiency gap. *Journal of Economic Literature*, 55(4):1486–1525.

Gilbert, B. and Zivin, J. G. (2014). Dynamic salience with intermittent billing: Evidence from smart electricity meters. *Journal of Economic Behavior & Organization*, 107:179–190.

Giraudet, L.-G., Houde, S., and Maher, J. (2018). Moral hazard and the energy efficiency gap: Theory and evidence. *Journal of the Association of Environmental and Resource Economists*, 5(4):755–790.

Greenstone, M. (2004). Did the clean air act cause the remarkable decline in sulfur dioxide concentrations? *Journal of Environmental Economics and Management*, 47:585–611.

Greenstone, M. and Hanna, R. (2014). Environmental regulations, air and water pollution, and infant mortality in india. *American Economic Review*, 104(10):3038–72.

Harrison, A. E., Hyman, B., Martin, L. A., and Nataraj, S. (2015). When do firms go green? Comparing price incentives with command and control regulations in India. *NBER Working Paper*, 21763.

Henderson, V. (1996). Effects of air quality regulation. *American Economic Review*, 86(4):789 – 813.

Jacobsen, G. D. (2019). An examination of how energy efficiency incentives are distributed across income groups. *The Energy Journal*, 40(6):171–198.

Jessoe, K. and Rapson, D. (2014). Knowledge is (less) power: Experimental evidence from residential energy use. *American Economic Review*, 104(4):1417–1438.

Karplus, V., Zhang, S., and Almond, D. (2018). Quantifying coal power plant responses to tighter so2 emissions standards in china. *Proceedings of the National Academy of Sciences*, 115(27):7004–7009.

Kotchen, M. J. (2017). Longer-run evidence on whether building energy codes reduce residential energy consumption. *Journal of the Association of Environmental and Resource Economists*, 4(1):135–153.

Martin, R., Muûls, M., and Wagner, U. J. (2016). The impact of the european union emissions trading scheme on regulated firms: What is the evidence after ten years? *Review of Environmental Economics and Policy*, 10(1):129–148.

McCoy, D. and Kotsch, R. (2020). Quantifying the distributional impact of energy efficiency measures. *GRI Working Paper*, 306.

Meyer, A. and Pac, G. (2017). Analyzing the characteristics of plants choosing to opt-out of the large combustion plant directive. *Utilities Policy*, 45:61–68.

Pon, S. (2017). The effect of information on TOU electricity use: an irish residential study. *The Energy Journal*, 38(6):55–79.

Prest, B. C. (2020). Peaking interest: How awareness drives the effectiveness of time-of-use electricity pricing. *Journal of the Association of Environmental and Resource Economists*, 7(1):103–143.

Ray, G. and Sunikka-Blank, M. (2013). *A Critical Appraisal of Germany's Thermal Retrofit Policy: Turning Down the Heat*. London: Springer.

RWI and microm (2020). RWI-GEO-GRID: Socio-economic data on grid level (wave 9). Version: 1. RWI – Leibniz Institute for Economic Research. Dataset. http://doi.org/10.7807/microm:V8.

Schmitt, S. and Schulze, K. (2011). Choosing environmental policy instruments: An assessment of the environmental dimension of EU energy policy. In Tosun, Jale, and Israel Solorio (eds). Energy and Environment in Europe: Assessing a Complex Relationship? European Integration online Papers (EIoP), Special Mini-Issue 1, Vol. 15, Article 9, http://eiop.or.at/eiop/texte/2011-009a.htm.

Sexton, S. (2015). Automatic bill payment and salience effects: Evidence from electricity consumption. *The Review of Economics and Statistics*, 97(2):229–241.

Singhal, P. (2019). Are Emission Performance Standards Effective in Pollution Control? Evidence from the EU's Large Combustion Plant Directive. DIW Berlin Discussion Paper, No. 1773.

Singhal, P. and Stede, J. (2019). Heat monitor 2018: Rising heating energy demand, thermal retrofit rate must increase. DIW Weekly Report, Volume 9, Issue 35/36, 303–312.

Stavins, R. N. (2006). Vintage-Differentiated Environmental Regulation. *Stanford Environmental Law Journal*, 25(1):29–63.

Tiefenbeck, V., Götte, L., Degen, K., Tasic, V., Fleisch, E., Lalive, R., and Staake, T. (2018). Overcoming salience bias: How real-time feedback fosters resource conservation. *Management Science*, 64(3):1458–1476.

Wager, S. and Athey, S. (2018). Estimation and inference of heterogeneous treatment effects using random forests. *Journal of the American Statistical Association*, 113(523):1228–1242.

Wätzold, F. (2004). SO_2 Emissions in Germany: Regulations to Fight Waldsterben. In W. Harrington, R. D. Morgenstern and T. Sterner (eds): Choosing Environmental Policies. Comparing Instruments and Outcomes in the United States and Europe. Washington DC: Resources for the Future, pp 23 - 40.

Weiß, D. and Michelsen, C. (2011). The improvement of housing conditions in post communist germany - market mechanisms and subsidy impacts. Conference paper. 51st Congress of the ERSA: 30 August - 3 September 2011, Barcelona, Spain.

Wichman, C. (2017). Information provision and consumer behavior: A natural experiment in billing frequency. *Journal of Public Economics*, 152:13–33.

Wynn, G. and Coghe, P. (2017). Europe's Coal-Fired Power Plant: Rough Times Ahead. Institute for Energy Economics and Financial Analysis.

Erklärung

Erklärung gemäß §4 Abs. 2

Hiermit erkläre ich, dass ich mich noch keinem Promotionsverfahren unterzogen oder um Zulassung zu einem solchen beworben habe, und die Dissertation in der gleichen oder einer anderen Fassung bzw. Überarbeitung einer anderen Fakultät, einem Prüfungsausschuss oder einem Fachvertreter an einer anderen Hochschule nicht bereits zur Überprüfung vorgelegen hat.

(Unterschrift, Ort, Datum)

Erklärung gemäß §10 Abs. 3

Hiermit erkläre ich, dass ich für die Dissertation folgende Hilfsmittel und Hilfen verwendet habe:

- STATA, R, Excel, LaTeX
- DeepL Übersetzer

Auf dieser Grundlage habe ich die Arbeit selbstständig verfasst.

(Unterschrift, Ort, Datum)